Exhibit 3

IN THE UNITED STATES DISTRICT COURT
FOR THE DISTRICT OF RHODE ISLAND

<table>
<tr><td>SHEET METAL WORKERS LOCAL NO. 20 WELFARE AND BENEFIT FUND, and INDIANA CARPENTERS WELFARE FUND, on behalf of themselves and all others similarly situated,
Plaintiffs,

v.

CVS PHARMACY, INC. and CAREMARK, L.L.C.,

Defendant.</td><td>Case No. 1:16-cv-00046-S</td></tr>
<tr><td>PLUMBERS WELFARE FUND, LOCAL 130, U.A., on behalf of itself and all others similarly situated,
Plaintiffs,

v.

CVS PHARMACY, INC. and CAREMARK, L.L.C.,

Defendant.</td><td>Case No. 1:16-cv-00447-S</td></tr>
</table>

EXPERT REBUTTAL REPORT OF MICHAEL P. SALVE, PH.D.

July 16, 2019

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I. INTRODUCTION AND SCOPE OF WORK

1. FTI Consulting ("FTI") was engaged by Williams & Connolly LLP ("Counsel") in connection with its representation of CVS Pharmacy, Inc ("CVS") and Caremark, L.L.C. ("Caremark"; collectively, "Defendants") in the above-referenced matters. I was engaged to provide expert opinions and analysis in this matters as set forth below.

2. I was asked to review the report submitted in this case by Plaintiffs' expert Dr. Conti ("Conti Report") and to offer opinions regarding issues pertaining to Dr. Conti's (1) damage theory, (2) methodology used to calculate damages for the 13 states and the District of Columbia (collectively, for simplicity, "the 14 states") with CVS data and (3) statistical analysis used to extrapolate damages to the 36 states without CVS data.[1]

3. My analyses, conclusions, and opinions are based solely on the work performed by me and those under my supervision, through the date of this expert report. I reserve the right to supplement the opinions should additional relevant information become available that bears on the analyses, conclusions, or opinions contained herein.

II. QUALIFICATIONS

4. I am a Senior Managing Director at FTI. My professional responsibilities include providing statistics, econometrics, economics, simulation, and financial modeling services in litigation.

5. I received my Ph.D. in economics from Boston College in 1995, specializing in applied econometrics and industrial organization. While I was in the doctoral program at Boston

[1] Expert Report of Rena Conti, Ph.D. in Support of Plaintiffs' Motion for Class Certification dated April 29, 2019 ("Conti Report"). Dr. Conti extrapolates to 36 rather than 37 states because there were no CVS stores in Wyoming during the period at issue. Conti Report ¶78, footnote 80.

College, I taught undergraduate courses in statistics and macroeconomic theory at Boston College and in microeconomic theory at Suffolk University. During the last eight years, I have taught two courses called "Law and Economics" and "Econometrics" in the graduate economics program at Hunter College, City University of New York in New York City.

6. In the graduate Econometrics course, some of the topics I cover are regression analysis, regression diagnostics, spurious regression, cointegrated time series models, statistical hypothesis testing, data cleaning, data matching, and model specification. In the graduate Law and Economics course, some of the topics I cover are class action litigation, event studies, and tests for causality.

7. I have testified at trial or arbitration four times and have been deposed twelve times as an expert witness in the last five years. These matters are listed in my Curriculum Vitae, which is attached as Appendix A. I have authored two publications in the last 10 years, which are also listed in Appendix A.

8. During the last 25 years, I have been involved in calculating economic damages in the context of litigation relating to a wide range of issues and businesses, including False Claims Act litigation in the healthcare industry, insurance coverage disputes, recalibration of Medicare Advantage risk scores, the use of artificial intelligence in identifying healthcare overpayments, government payor reimbursement for prescription drugs, opioid distribution networks, and healthcare reimbursement audits.

9. I have been retained by some of the largest health insurance companies in the country to work with their claims data and query their systems for indicia of fraudulent transactions. I have also worked with some of the largest pharmacies and pharmaceutical companies in the country on their internal database architecture and the ability to link these

databases to external marketing and call note databases. I have been qualified as an expert and have presented testimony in federal court in a qui tam false claims act matter regarding healthcare data issues, and I have been deposed by the U.S. Department of Justice in another qui tam false claims act matter relating to quantitative and statistical analyses regarding healthcare data. I have also been cross-examined by the New York State Office of the Medicaid Inspector General on issues relating to the alleged identification of overpayments.

10. In the last five years, I have been invited to present on the topic of advanced healthcare data analytics to hundreds of healthcare professionals in Los Angeles, New York and New England in various forums including the New England Healthcare Internal Auditors Annual Compliance & Audit Conference, the Health Care Compliance Association and the Healthcare Financial Management Association.

11. FTI is compensated at the rate of $710 per hour for my services in this matter. The hourly rates of my supporting staff range from $350-570. No portion of my fees is dependent upon the outcome of this case.

12. My opinions are based on my personal knowledge, education, training and experience, information produced in this litigation, and the review and analysis of documents cited in this report and referenced in Appendix B.

III. MATERIALS REVIEWED

13. I have reviewed certain information of the type and nature customarily relied upon by economists and applied econometricians in presenting the information contained in this report. A detailed list of the materials I reviewed is contained in Appendix B.

IV. BACKGROUND

A. Description of the CVS Reimbursement Transaction Data

14. I received 27 data files containing more than one billion lines of CVS reimbursement transactions ranging from November 9, 2008 through December 31, 2015 (collectively, "CVS Reimbursement Data"). The CVS Reimbursement Data were limited to transactions in the following thirteen states and the District of Columbia: Arizona; California; Florida; Georgia; Illinois; Indiana; Massachusetts; Maryland; New Jersey; New York; Ohio; Pennsylvania; and Texas. In addition to these 27 data files, I received two supplemental files containing Coordination of Benefits ("COB") pharmacy transactions. I understand that Dr. Conti analyzed the CVS Reimbursement Data, which contained CVS reimbursement transactions from Pharmacy Benefit Managers ("PBMs") to CVS for drugs that were included in CVS's Health Savings Pass Program ("HSP"). In total, the files that I received contained 1,003,855,926 lines of data.[2]

B. Overview of Dr. Conti's Damage Theory for Third Party Payors for the 14 States with CVS Reimbursement Data

15. Dr. Conti was retained to calculate damages for third-party payors ("TPPs") who are proposed class members in this matter.[3] Dr. Conti states that her damage calculations must take into account "the overpayment of At-Issue Drugs paid for by TPPs due to inflated U&C prices that did not account for HSP prices."[4]

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[2] Each row of transaction data had a Bates number (DCVS – 00000000001 through DCVS – 01003855926).

[3] Conti Report, ¶8.

[4] Conti Report, ¶10.

16. Dr. Conti creates five theoretical equations to model "Plaintiff Expenditures" in an effort to calculate proposed class members' alleged damages.[5] Dr. Conti presents five theoretical equations to measure the proposed class TPPs' (1) actual expenditures and (2) "but for" expenditures if CVS had reported HSP prices as U&C prices. She then attempts to apply these five "Plaintiff Expenditure" equations to the CVS Reimbursement Data for 14 states to calculate out-of-pocket losses[6] for the proposed class TPPs. Dr. Conti does not take into account any of the contractual pricing terms that were negotiated between CVS and the PBMs or the PBMs and the TPPs.[7]

C. Overview of Dr. Conti's Extrapolation of Damages to the 36 States without CVS Reimbursement Data

17. The CVS Reimbursement Data that Dr. Conti used contains transactions for only 14 of the 50 states. Dr. Conti attempts to take her quantitative damage results from these 14 states and apply them to the remaining 36 states using regression analysis. Simply stated, the regression analysis attempts to take her over-reimbursement calculations for CVS for the 14 states, and correlate these over-reimbursement amounts to various macroeconomic demographic data she selected arbitrarily for each of the 14 states. Dr. Conti then attempts to take these correlations and "back into" what the over-reimbursement calculations would be to CVS in the 36 states using only these arbitrary macroeconomic, demographic data for these 36 states. Dr. Conti calls this an extrapolation analysis.[8]

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[5] Conti Report, pp. 21-23, equations (1) – (5).

[6] Conti Report, ¶62.

[7] Deposition of Dr. Rena Conti, 152:9-15 and 152:22-153:3.

[8] Conti Report, p. 31, Section 4.

18. It is important to note, however, that Dr. Conti does not extrapolate payor-specific damages due to overpayments made by certain TPPs in the 14 states to the same TPPs in the remaining 36 states. Instead, she calculates monthly state-level CVS alleged over-reimbursement calculations for 14 states and tries to extrapolate them to the other 36 states. The regression analysis assumes that CVS over-reimbursements are correlated with her arbitrary state-level demographic information on macroeconomic variables such as state population, percentage of the state population that is male, and state median household income.[9]

V. SUMMARY OF OPINIONS

19. Based on my review of the Conti Report, Dr. Conti's deposition transcript, the CVS data provided to me by counsel, and the demographic data and computer scripts provided from Dr. Conti, I have the following opinions.

20. It is my opinion the Dr. Conti's proposed methodology to calculate out-of-pocket losses (in the 14 states for which she has CVS reimbursement data) for the proposed class of TPPs using the CVS reimbursement data is deficient, and its results are unreliable.

21. Further, it is my opinion that even if Dr. Conti were able to calculate reliable damages in the 14 states mentioned above, the statistical model used by Dr. Conti to calculate out-of-pocket losses for the proposed class of TPPs (in the 36 states for which she does not have CVS data) is fatally flawed, and its results are misleading and unreliable.

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[9] Conti Report, Attachment E, ¶B.2.c.

A. Dr. Conti's damage methodology does not calculate an appropriate out-of-pocket loss to TPPs for purposes of calculating economic damages for alleged class members

22. Dr. Conti's quantification of class-wide damages relies solely upon the CVS Reimbursement Data, which does not necessarily reflect the amount that the TPPs actually paid CVS for any of the drugs in Dr. Conti's analysis.[10] In fact, when Dr. Conti is pressed on this important point, she admits that she just assumes that the data reflect what the TPPs paid CVS.[11] Dr. Conti further admits that the data, and her model, may not capture *any* payments made by the proposed class TPPs, but rather, may capture *only* amounts paid by the PBMs to CVS.[12] This inherent feature of the data causes her intended calculations of out-of-pocket loss to TPPs (for purposes of calculating economic damages) to be meaningless.

23. Additionally, as Dr. Conti states, PBMs are companies that serve as middlemen between the proposed class TPPs and CVS, and the PBMs' business relationships are governed by negotiated contracts.[13] In Figure 1 of the Conti Report, there is no direct payment link between the TPPs (proposed class members) and the Pharmacy (CVS). Figure 1 shows that the PBM sits between the TPPs and the Pharmacy and that *both* the payments from the TPP to the PBM and the payments from the PBM to the Pharmacy are negotiated. One cannot assume that the TPP's negotiated payments to the PBM are exactly the same as the PBM's negotiated payments to the Pharmacy.

24. Without having relevant and reliable data that show the amounts that were paid by the TPPs (proposed class members) to their PBMs, neither Dr. Conti nor anyone else can

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[10] Deposition of Dr. Rena Conti, 153:13-22.

[11] Deposition of Dr. Rena Conti, 153:13-17.

[12] Deposition of Dr. Rena Conti, 153:9-12.

[13] Conti Report, ¶26 and p. 11, Figure 1.

quantify the alleged economic damages in this matter. This inherent deficiency in the data cannot be undone through theoretical damage equations, regardless of how sophisticated or elegant they may appear.

B. Even if Dr. Conti's damage calculations were reliable for the 14 states, her statistical model is fatally flawed and cannot be used to extrapolate damages to the other 36 states

25. This section lists the many reasons why Dr. Conti's statistical regression model and its data inputs cannot be used to extrapolate any damage calculations from the 14 states to the 36 states for which there is no CVS reimbursement data.

i. Dr. Conti destroys the integrity of her extrapolation model by arbitrarily manufacturing most of the data used in her GLM regression analysis

26. Dr. Conti manufactures monthly demographic data to perform her GLM regression analysis and extrapolation of damages.[14] Dr. Conti sums her transaction-level damage results by month and then takes her monthly damages by state and associates them with state-level demographic factors (such as median income, % of the state population that is male by age group), total retail prescription sales, Medicaid dollars, and per capita prevalence of CVS pharmacies.[15] Most of these variables that Dr. Conti includes in her GLM regression analysis are not *monthly* data but are *annual* data that Dr. Conti spreads across a year by using three different methods. She sometimes spreads identical values across the 12 months within a year, or she "peanut butter smooths" steady, linear growth across the 12 months (meaning that she uses a

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[14] In statistical modelling, the generalized linear model ("GLM") is a type of regression model that is often used because it is more flexible than the more common Ordinary Least Squares ("OLS") regression models. GLM models will measure the non-linear correlations between a dependent variable and one or more independent variables.

[15] Conti Report, Attachment E, ¶1.

growth rate to create data values that grow smoothly from one annual data point to the next annual data point), or she pro-rates quarterly data values to create monthly values.[16] These three smoothing methods manufacture monthly data when no such numbers were ever reported in the source data she relies upon.

27. The table below outlines the variables Dr. Conti uses in her monthly GLM regression analysis and indicates the manufactured frequency of the data that Dr. Conti uses in her analysis, along with the source data's actual reported frequency.

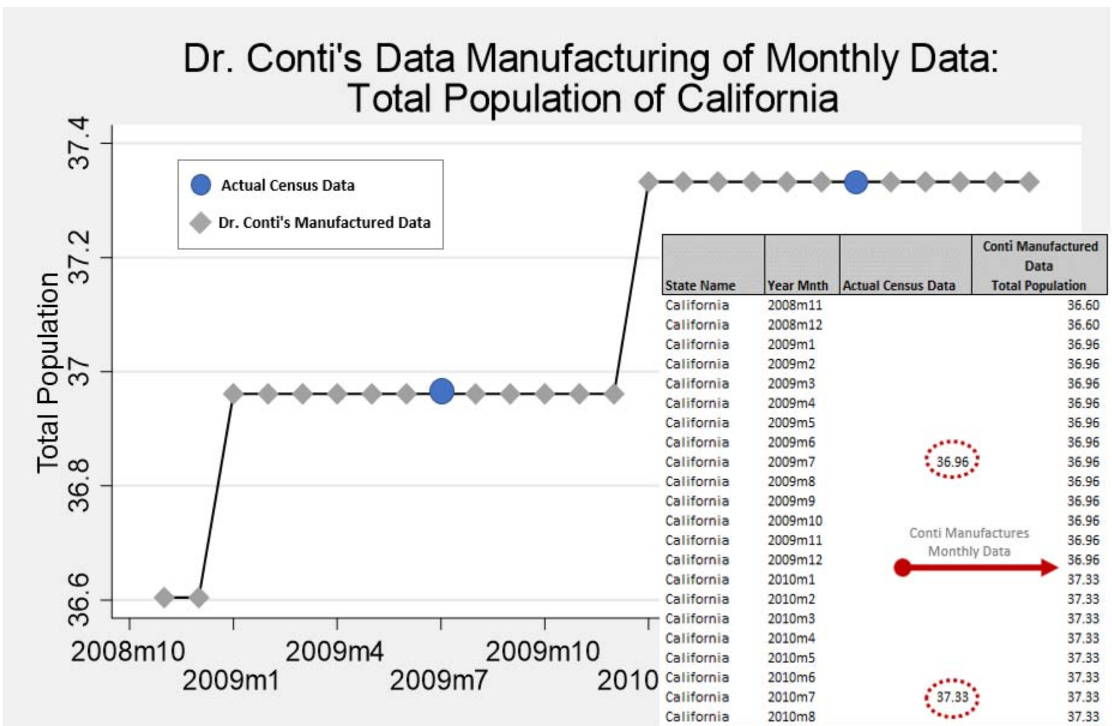
[16] Conti Report, Attachment E, ¶B.2.c.

Figure 1

Name	Comment/Description	Frequency in Conti Analysis	Frequency in Data Source
male_population_pct_m	Male Population % for Each Month	Monthly	Yearly
medinc_m	Median Income by Month	Monthly	Yearly
pctinscov_m	% Insured by Month. Missing header. Assumes left to right is 2008 to 2016. Monthly value calculated by smoothening yearly values.	Monthly	Yearly
tot_med_dol	Total_Medicaid_HSP_Dollars	Monthly	Quarterly
uspharsales	US Pharma Sales	Monthly	Monthly
lcvspc	log(CVS stores/total population)		
pct_age_05_9_m	% Between Ages 5 and 9 for Each Month	Monthly	Yearly
pct_age_10_14_m	% Between Ages 10 and 14 for the Month	Monthly	Yearly
pct_age_15_19_m	% Between Ages 15 and 19 for the Month	Monthly	Yearly
pct_age_20_24_m	% Between Ages 20 and 24 for the Month	Monthly	Yearly
pct_age_25_29_m	% Between Ages 25 and 29 for the Month	Monthly	Yearly
pct_age_30_34_m	% Between Ages 30 and 34 for the Month	Monthly	Yearly
pct_age_35_39_m	% Between Ages 35 and 39 for the Month	Monthly	Yearly
pct_age_40_44_m	% Between Ages 40 and 44 for the Month	Monthly	Yearly
pct_age_45_49_m	% Between Ages 45 and 49 for the Month	Monthly	Yearly
pct_age_50_54_m	% Between Ages 50 and 54 for the Month	Monthly	Yearly
pct_age_55_59_m	% Between Ages 55 and 59 for the Month	Monthly	Yearly
pct_age_60_64_m	% Between Ages 60 and 64 for the Month	Monthly	Yearly
pct_age_65_69_m	% Between Ages 65 and 69 for the Month	Monthly	Yearly
pct_age_70_74_m	% Between Ages 70 and 74 for the Month	Monthly	Yearly
pct_age_75_79_m	% Between Ages 75 and 79 for the Month	Monthly	Yearly
pct_age_80_84_m	% Between Ages 80 and 84 for the Month	Monthly	Yearly
pct_age_85_over_m	% Over Age 85 for Each Month	Monthly	Yearly
year			
month			
tp	Rounded value of total population in 1000s.	Monthly	Yearly

28. For example, Dr. Conti took *annual* total state population data as reported by Census.gov[17] and manufactured monthly data by flattening out the annual data into a monthly frequency, thereby creating false, never-reported, data points. These artificial-looking data points that have no variation within a year can be seen in the chart below, which shows Dr. Conti's "monthly" total populations for California for 2009-2010 per Dr. Conti's model. It is also important to note that because Dr. Conti manufactured monthly data, the total population figure in January of each year artificially jumps up from the December figure of the previous year.

Figure 2



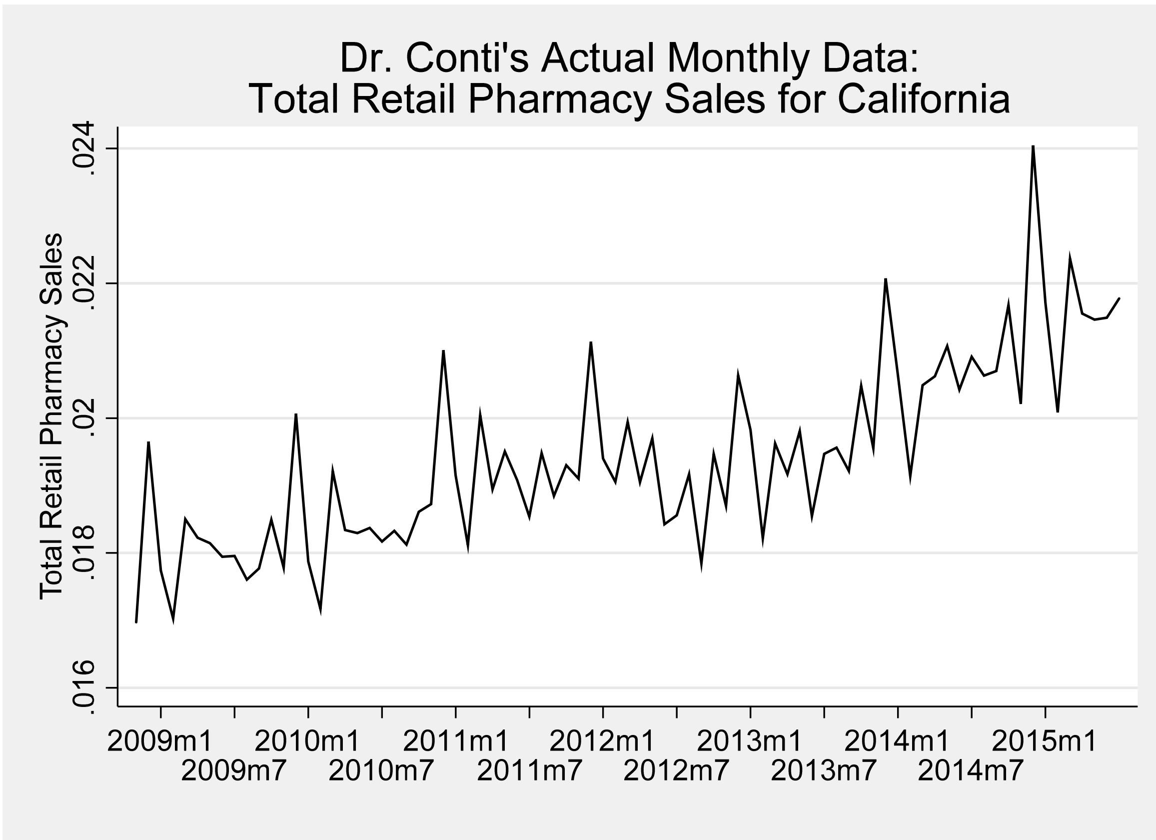
State Name	Year Mnth	Actual Census Data	Conti Manufactured Data Total Population
California	2008m11		36.60
California	2008m12		36.60
California	2009m1		36.96
California	2009m2		36.96
California	2009m3		36.96
California	2009m4		36.96
California	2009m5		36.96
California	2009m6		36.96
California	2009m7	36.96	36.96
California	2009m8		36.96
California	2009m9		36.96
California	2009m10		36.96
California	2009m11		36.96
California	2009m12		36.96
California	2010m1		37.33
California	2010m2		37.33
California	2010m3		37.33
California	2010m4		37.33
California	2010m5		37.33
California	2010m6		37.33
California	2010m7	37.33	37.33
California	2010m8		37.33

29. The monthly manufactured population data chart above stands in stark contrast to a chart showing a variable with actual monthly values. For example, below is a chart that shows the actual source data for monthly retail pharmacy sales in California per Dr. Conti's model.

[17] Conti Report, Attachment E, ¶B.2.c.

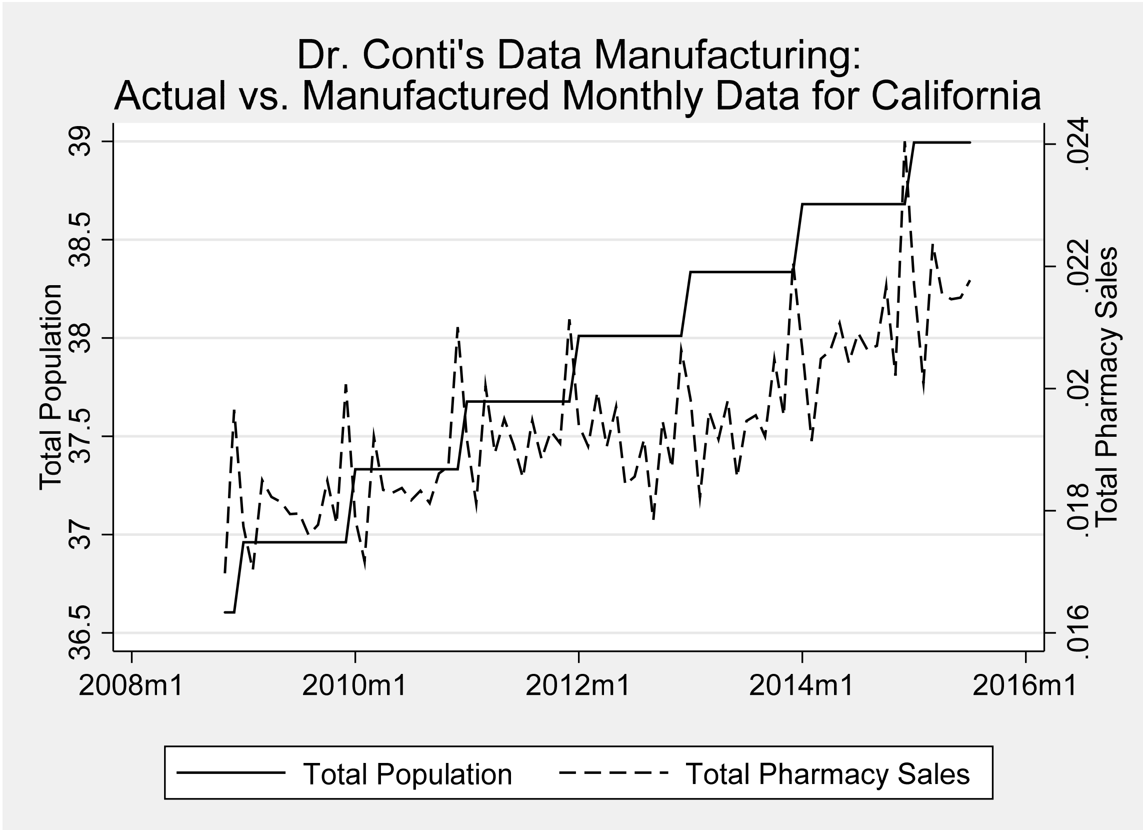
Here, one can see the *natural* spikes of retail sales in December of each year, to be contrasted with Dr. Conti's *manufactured* January spikes in the prior chart above.

Figure 3



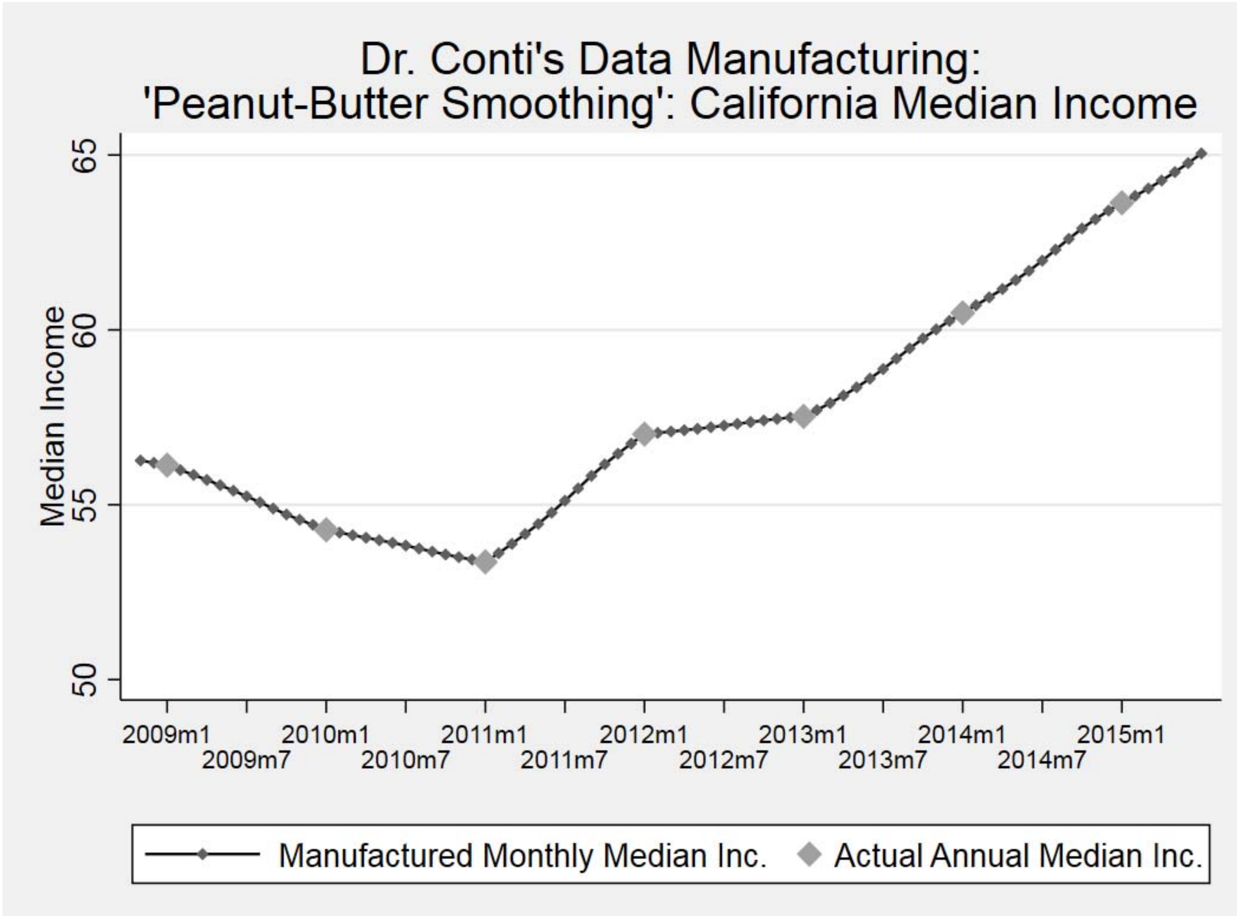
30. When we overlay the manufactured monthly frequency population data with actual monthly pharmacy sales data in the chart below, we can observe the artificial data that Dr. Conti manufactures and transfers into her GLM regression analysis.

Figure 4



31. Dr. Conti is inconsistent with her data manufacturing. For some of the variables, Dr. Conti elects to have static, duplicative manufactured monthly data that jumps from December to January, whereas for other variables, she elects to "peanut butter smooth" a growth rate for the manufactured monthly data. In the figure below, I show Dr. Conti's inconsistent monthly data manufacturing process for her median income values for California, where she arbitrarily creates linear growth between the annual data points, in contrast with her data manufacturing process for the total population, which jumps up every January.

Figure 5



32. For Dr. Conti's Total Medicaid HSP Spending data, she again is inconsistent with her data manufacturing process and engages in an elaborate data manufacturing process of transforming this *quarterly* Medicaid data from Medicaid.gov into *monthly* data.[18] In this data manufacturing process, Dr. Conti "normalizes" and pro-rates these quarterly data on a daily basis to create her artificial monthly Medicaid HSP spending variable. This is the third type of data manufacturing process in her regression and extrapolation process.

[18] Conti Report, Attachment E, ¶B.2.d.

33. These various data manufacturing processes have large quantitative impacts, intended or unintended, on Dr. Conti's GLM analysis. Dr. Conti's arbitrary manufacturing of monthly data changes the correlation coefficients, standard errors, R-square statistics, and the resulting GLM regression's extrapolated damages.[19]

34. For example, by shifting Dr. Conti's model to an annual model, her predicted damages for Utah would be reduced from $40.6 million to $14.9 million, a $25.7 million or 63% reduction. For Rhode Island, this change would lead to a $59.6 million or 46% increase in damages from $129.8 million to $189.4 million.

ii. Dr. Conti fails to account for outliers in the data and fails to investigate how these outliers bias her results

35. Dr. Conti could have easily detected that her data has outliers and systemic anomalies that are not explained by her GLM model's explanatory variables. A casual review of Dr. Conti's own damage tables[20] shows that Massachusetts (MA) is an outlier, a simple analysis that Dr. Conti herself failed to perform.[21]

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[19] Marcellino, M. (1999). Some Consequences of Temporal Aggregation in Empirical Analysis. *Journal of Business & Economic Statistics*, 17(1), pp. 129-136.

[20] Conti Report, Attachment C.2.c.

[21] Deposition of Dr. Rena Conti, 271:19-272:2.

explanation before submitting your report but after noticing this result from Massachusetts?
A I'm not following your question, sir.
Q After finding this result for Massachusetts --
A You found this result for Massachusetts, sir. The one that we're talking about right now.
Q Well, I'll just direct you to attachment C.2.c of your report. After calculating in that attachment a damages figure of $153,302,965.07 for Massachusetts, did you analyze whether population or elevated drug use or the number of stores explained why those damages were so high?
A Again, based on the primitives of my methodology, it's likely because there were many prescriptions that were -- that were eligible for the HSP price that were transacted at a higher price.
Q Did you use your calculated damages figure for Massachusetts as part of your statistical extrapolation?
A Yes.
Q Did you consider whether it would be appropriate to exclude the Massachusetts result as an outlier before using it in your statistical

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extrapolation?
A No, I did not.
Q Why not?
A Because my model accounts for the count of stores and the volume of prescriptions that were specifically eligible for the HSP price in the statistical model.
Q Does the high damages figure specific to Massachusetts give you any cause for concern that there may be something unique to your analysis of Massachusetts that is causing unrealistically elevated damages for that state?
A I don't agree with your characterization.
Q Does the result you found in your damages calculation for Massachusetts give you any cause for concern that there may be a flaw in your analysis of Massachusetts damages?
A So again, there are reasonable reasons why we may see an elevated damage estimate in specific states.
Q Are you aware of what reasons there would be for your result of 153,302,965 in damages for Massachusetts as compared to approximately $50 million for the next highest state?
A I have already provided that reasonable

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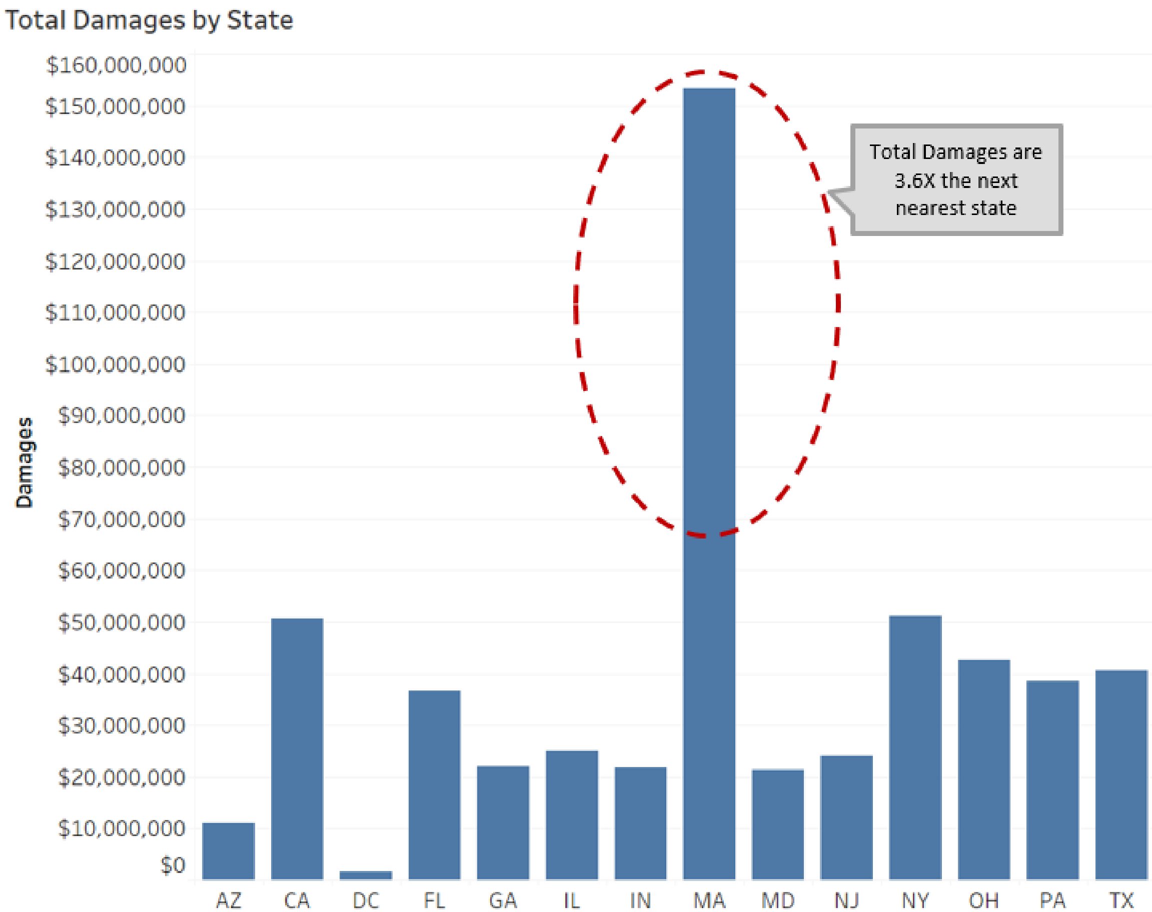
36. If Dr. Conti had performed this simple analysis, she would have discovered that her own damage model has MA accounting for $153.3 million or 28.4% of the total $540.2 million of alleged damages in the 14 states. By contrast, California (CA) has $50.7 million of alleged damages, one-third of the total damages of MA, yet CA has an average population that is 5.7 times that of MA.[22] To put this outlier into further context, Dr. Conti's own demographic data shows that MA has 6.6 million people or 3.6% of the total population of 184 million in the 14 states while having 28.4% of the total damages, meaning that Dr. Conti attributes per capita damages to MA that are 7.9 times more than the overall average per capita damages. Simple visualizations of Dr. Conti's damages also demonstrate the outlier nature of MA.

[22] An average of 37.9 million people in CA versus MA's average population of 6.6 million.

Figure 6



37. Dr. Conti did not investigate whether it is appropriate to include MA in her statistical model or to exclude MA as an outlier from her analysis and extrapolations.[23] However, if she had investigated the impact of MA on her extrapolation model, she would have discovered that the mere inclusion of MA into her GLM regression model biases the predicted extrapolated damages for the other *non-MA* states by $69 million or 9.2%. Dr. Conti's deficient model artificially inflates damages upwards by 9.2%, causing non-MA states to be biased upward with total predicted damages of $833 million when they otherwise would have been $754 million if MA had been excluded from the analysis.

[23] Conti Deposition 271:19-272:2.

iii. Dr. Conti's predicted damages by state demonstrate outliers and illogical results that are unexplained by her model's "explanatory" variables

38. Dr. Conti failed to assess her model's *predicted* damages for outliers, illogical results, and other anomalies that are not explained by her model's explanatory variables. For example, MA's very high per capita damage of 7.9 times more than the overall average per capita damages is not explained by Dr. Conti's explanatory variables. During her deposition, Dr. Conti conjectured that there might be "reasonable reasons" why MA has elevated damages relative to other states,[24] such as the number of CVS stores in MA[25] or the volume of prescriptions.[26] Based on a careful review of her explanatory variables, however, there appear to be no such "reasonable reasons."

39. The following simple visualizations show Dr. Conti's damages by state, across some of her explanatory variables. These visualizations do not provide "reasonable reasons" for the elevated damages in MA relative to other states and, in fact, are in direct contradiction to the suggestions made by Dr. Conti in her deposition testimony.[27]

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[24] Conti Deposition 272:14-20.

[25] Conti Deposition 268:10-14.

[26] Conti Deposition 272:4-7.

[27] Conti Deposition 272:14-20.

Figure 7

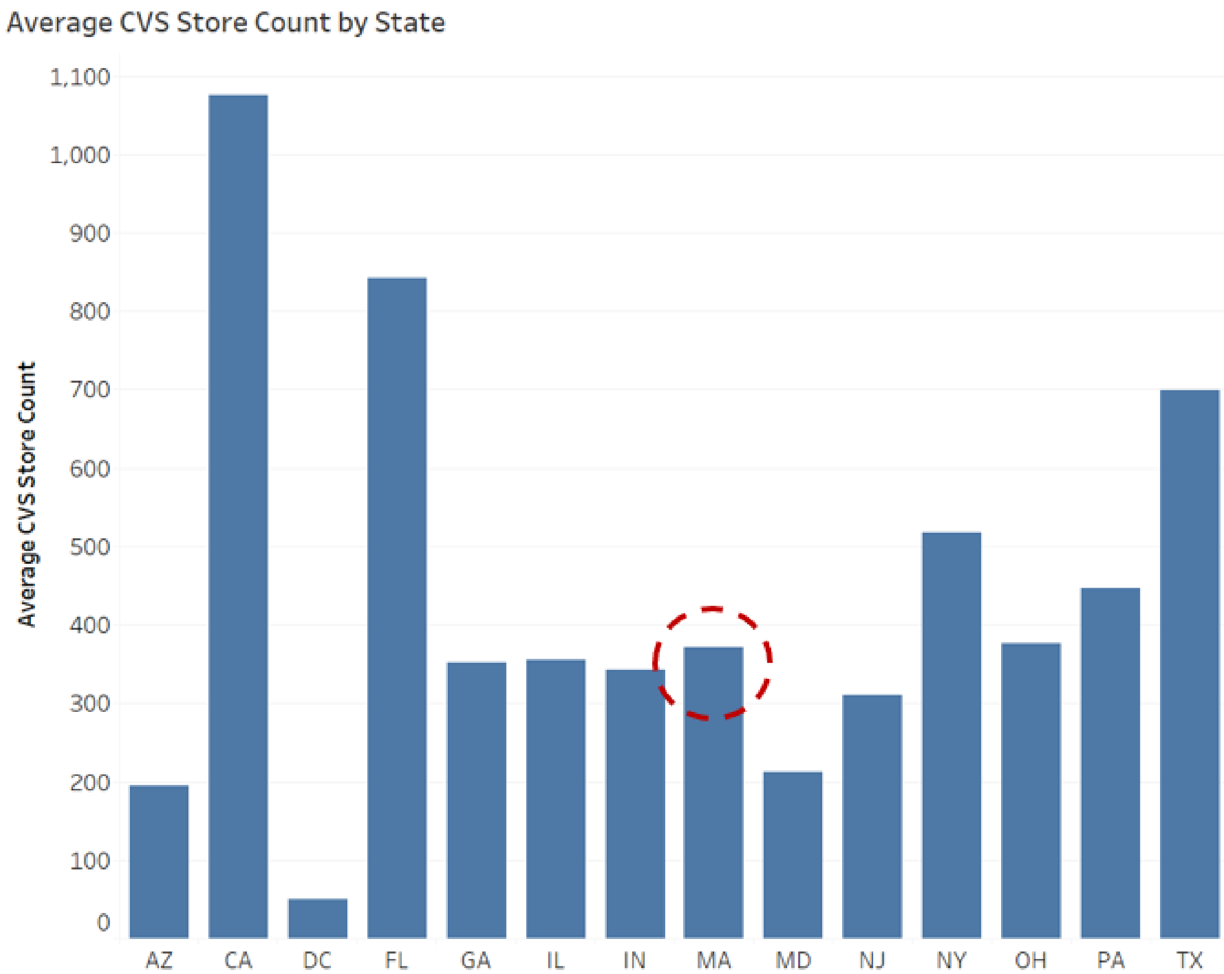

Average CVS Store Count by State
Average CVS Store Count
1,100
1,000
900
800
700
600
500
400
300
200
100
0
AZ
CA
DC
FL
GA
IL
IN
MA
MD
NJ
NY
OH
PA
TX

Figure 8

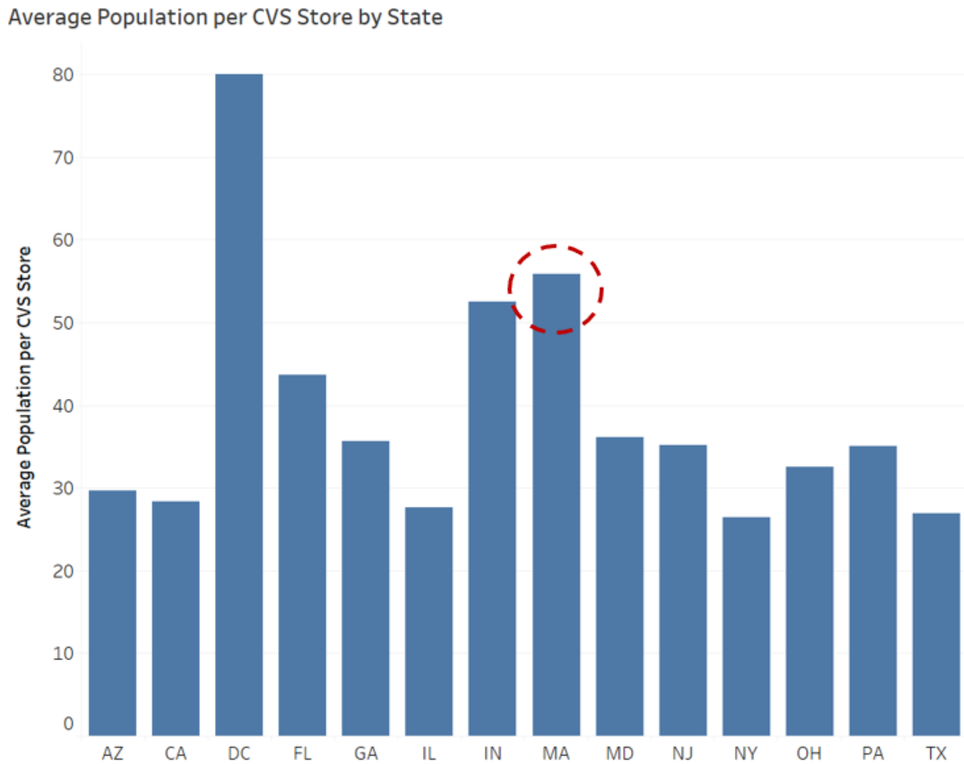
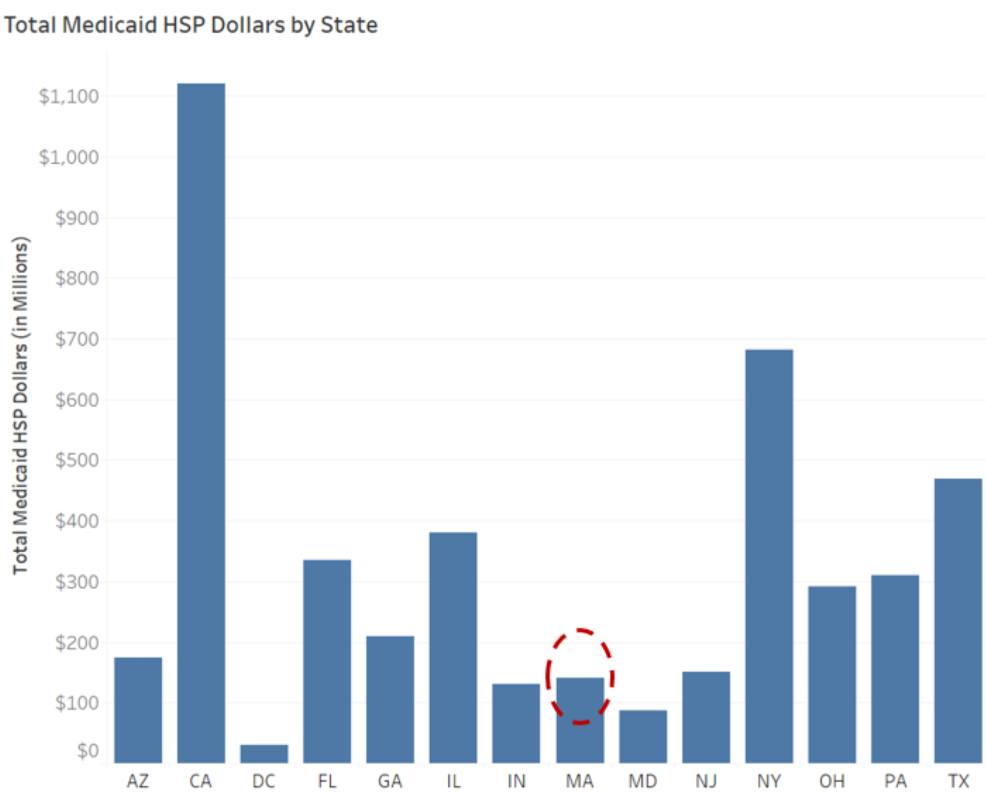
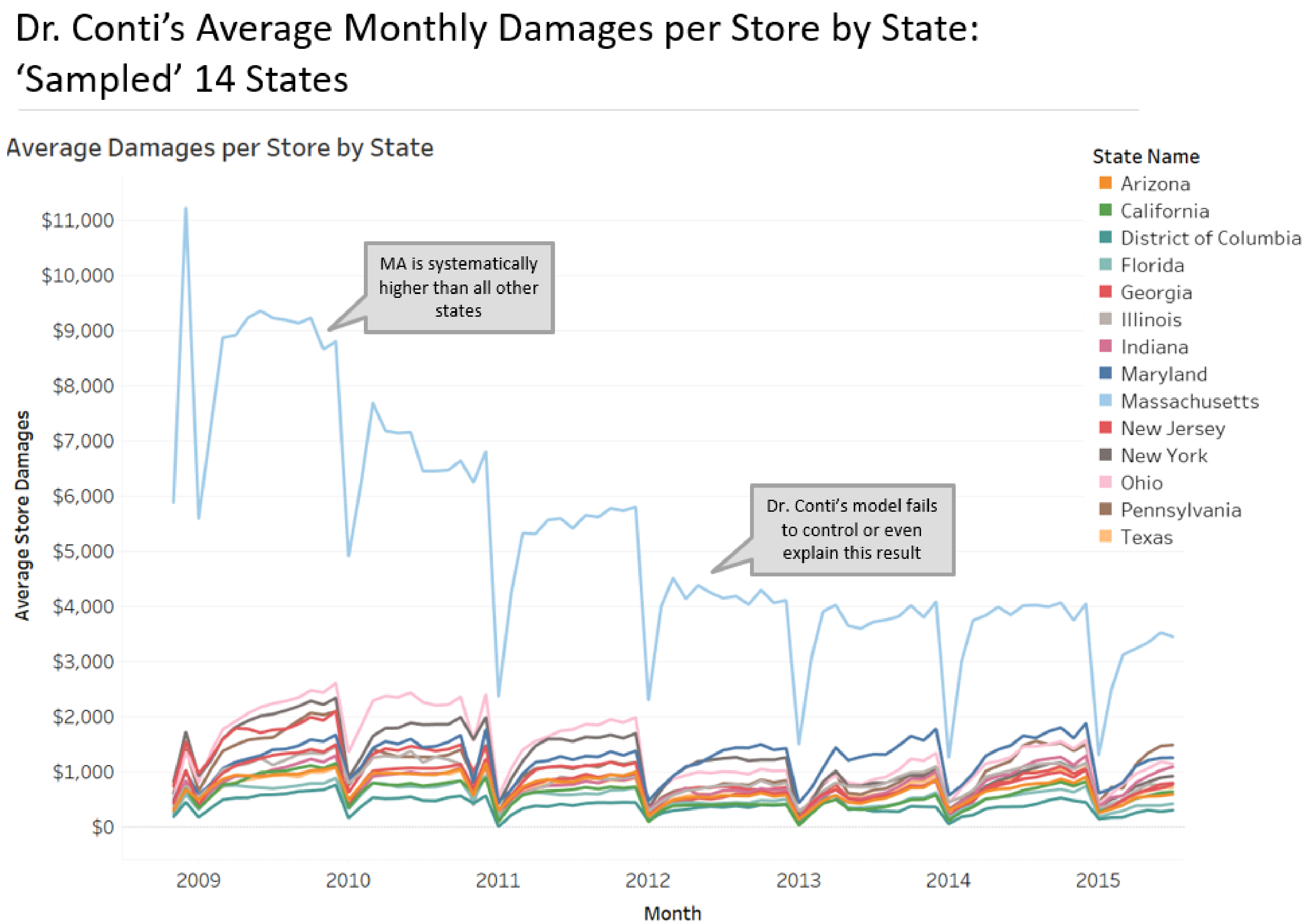


Figure 9



40. The next chart demonstrates how Dr. Conti's damage estimates for MA (which are not generated by her GLM regression model) are systemically higher than all the other 14 "sampled" states (i.e., the states in the CVS Reimbursement Data). Additionally, this shows unexplained seasonality and trending damage patterns over time for MA and the 13 other states.

Figure 10


Dr. Conti's Average Monthly Damages per Store by State: 'Sampled' 14 States
Average Damages per Store by State
MA is systematically higher than all other states
Dr. Conti's model fails to control or even explain this result
Average Store Damages
$11,000
$10,000
$9,000
$8,000
$7,000
$6,000
$5,000
$4,000
$3,000
$2,000
$1,000
$0
2009
2010
2011
2012
2013
2014
2015
Month
State Name
Arizona
California
District of Columbia
Florida
Georgia
Illinois
Indiana
Maryland
Massachusetts
New Jersey
New York
Ohio
Pennsylvania
Texas

41. These prior charts show that Dr. Conti's *actual* damage calculations by state contain outliers, anomalies that are all present *before* she performs her regression analysis and extrapolation to the other 36 states. Thus, the inputs Dr. Conti uses for her regression analysis are deficient and unreliable, from the outset.

42. Dr. Conti again admits that she has not looked at how her model predicts damages within a state over time or specifically how it predicts damages within individual states.[28] Again, if Dr. Conti had performed this analysis or even happened to review the table in Attachment C.4 of her report, it would have become apparent that her model is not predicting damages reliably.

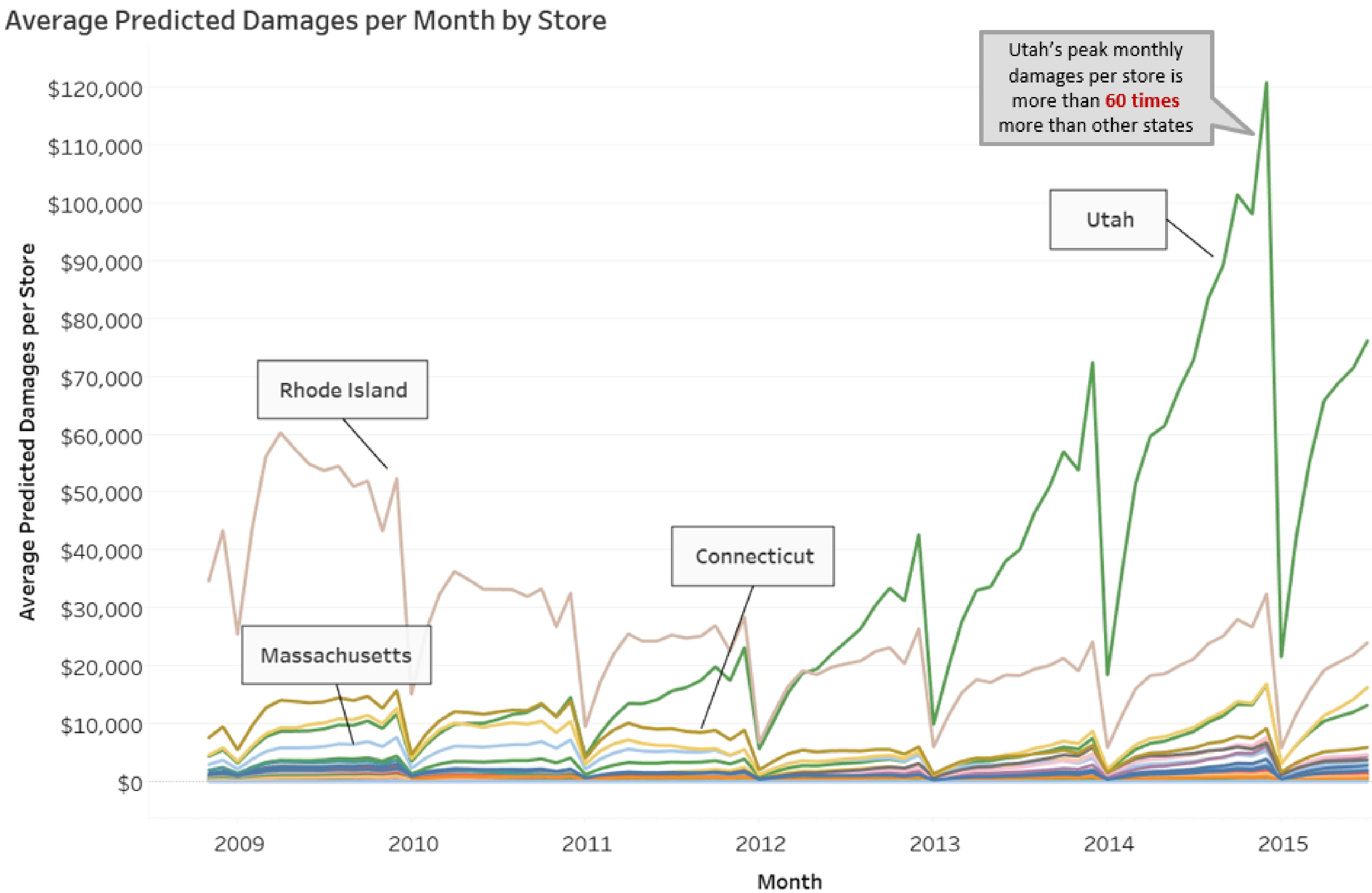
43. For example, Dr. Conti extrapolates and predicts $129.8 million of damages in Rhode Island (RI), a state with an average population of 1.05 million people and an average CVS store count of 62. This high damage amount for a small state is contrasted against New York (NY) with an average population of 19.5 million, average CVS store count of 517, and damages of $51.2 million. Dr. Conti estimates damages in RI that are 2.5 times those of NY, even though RI has 1/20th the population of New York and 1/8th the number of CVS stores.

44. The figure below shows Dr. Conti's *predicted* damages (using her regression analysis) per store per month by state. The chart clearly shows that Dr. Conti's model is not predicting damages reliably by state or over time. For example, Rhode Island and Utah are predicted to have damages per store per month that are multiples larger than the other states. In fact, Utah, during its peak damage month per Dr. Conti's regression model, has average store damages that are more than 60 times higher than the average monthly damages per store of some other states.

[28] Conti Deposition 278:4-12.

Figure 11

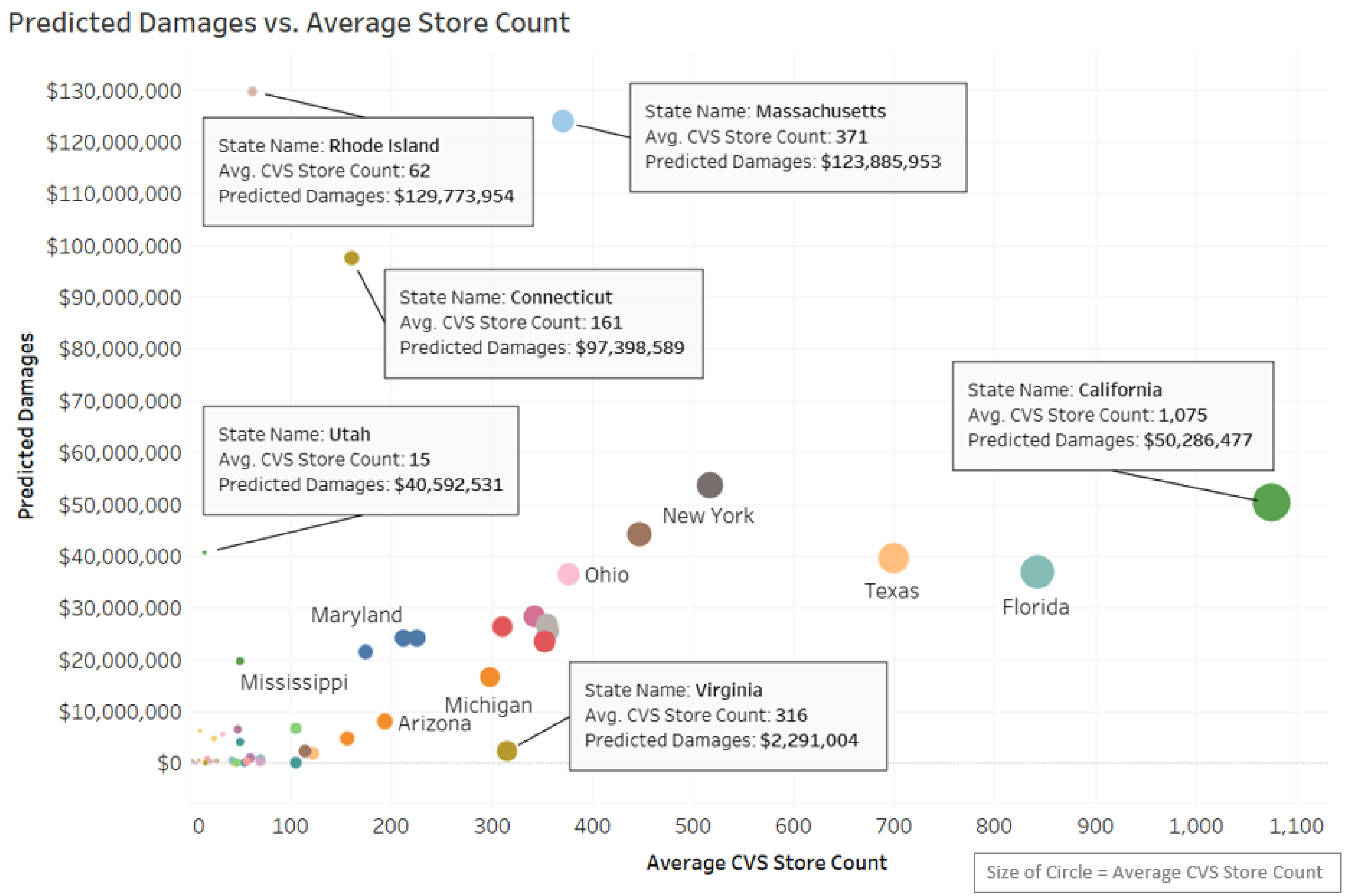
Dr. Conti's Average Monthly *Predicted* Damages per Store by State: All States



45. To further illustrate Dr. Conti's deficient methodology and unreliable predictions, I show the scatter plot below. This scatter plot details Dr. Conti's total predicted damages by state on the vertical axis and the state's average CVS store count on the horizontal axis. From the plot, we observe that Dr. Conti predicts California to have $50.3 million in damages, with an average of 1,075 CVS stores, which is only $9.7 million more than Utah which has 1,060 fewer stores. To put this into context, Dr. Conti estimates that Utah's stores are generating on average $2,706,169 in damages relative to California's stores that generate a mere $46,788 in damages. This is 58 times the per store damages in Californa relative to Utah. I have included a summary table of Dr. Conti's predicted damages by state along with many of her "explanatory" variables by state in Appendix C of this report.

Figure 12

Scatter Plot of Predicted Damages vs. Average Monthly Number of CVS Stores



iv. Dr. Conti's GLM regression model does not account for spurious (or nonsensical) correlations contained in the manufactured data she uses

46. Dr. Conti's regression model reports meaningless results for reasons that are described in basic undergraduate econometrics textbooks.[29] That is, Dr. Conti creates a regression model with dependent and explanatory variables that have no meaningful or causal relationship between them, despite reporting a high R-square statistic.[30]

> We noted in Chapter 1 that one of the important types of data used in empirical analysis is **time series** data. In this and the following chapter we take a closer look at such data not only because of the frequency with which they are used in practice but also because they pose several challenges to econometricians and practitioners.
>
> *First,* empirical work based on time series data assumes that the underlying time series is **stationary.** Although we have discussed the concept of stationarity intuitively in Chapter 1, we discuss it more fully in this chapter. More specifically, we will try to find out what stationarity means and why one should worry about it.
>
> *Second,* in Chapter 12, on autocorrelation, we discussed several causes of autocorrelation. Sometimes autocorrelation results because the underlying time series is nonstationary.
>
> *Third,* in regressing a time series variable on another time series variable(s), one often obtains a very high R^2 (in excess of 0.9) even though there is no meaningful relationship between the two variables. Sometimes we expect no relationship between two variables, yet a regression of one on the other variable often shows a significant relationship. This situation exemplifies the problem of **spurious,** or **nonsense, regression,** whose nature will be explored shortly. It is therefore very important to find out if the relationship between economic variables is spurious or nonsensical. We will see in this chapter how spurious regressions can arise if time series are not stationary.
>
> *Fourth,* some financial time series, such as stock prices, exhibit what is known as the **random walk phenomenon.** This means the best prediction
>
> 792

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[29] Guajarati, D. (2004). *Basic Econometrics, (4th Ed.)*. McGraw-Hill, p. 792. For example, Gujarati's Basic Econometrics warns that spurious regressions can arise if time series are not stationary. I performed a series of panel data stationarity tests on Dr. Conti's explanatory variables and found many of them are not stationary.

[30] Conti Report ¶79. Dr. Conti suggests the regression model is doing well solely on the correlation of .941 and corresponding R-square of .886.

47. Dr. Conti describes that she uses claim-level CVS data. However, instead of using this claim-level data in her regression analysis, she aggregates nearly a billion individual pharmacy transactions for HSP-eligible drugs into monthly totals by state. This monthly aggregation of her damage calculations completely detaches these data from the very data and factors she uses to calculate her transaction level alleged damages. She then uses these monthly totals as her dependent variable in her GLM regression model[31] and attempts to associate them with the following explanatory variables:

- Total Retail Prescription Sales Data – Monthly total retail pharmacy sales data from the Federal Reserve
- Demographic Data – Annual state demographic data from Census.gov; these include total population, male population %, % population by age, and median income, % population covered by private health insurance.
- Medicaid Claims Data – quarterly utilization data from Medicaid.gov, that was transformed, normalized, and manipulated to yield monthly totals for the HSP formulary list.
- CVS Pharmacy Counts – monthly CVS pharmacy counts by state from the CMS National Plan and Provider Enumeration System (NPPES) system.

48. These four broad categories of explanatory variables are not driving or causing Dr. Conti's alleged damage amounts. Dr. Conti has provided no evidence or explanation as to how her explanatory variables would be causally linked to her alleged damages. For example, it is unclear how the male population percentage for a given state causes an *increase* in damages for some states but then also causes a *decrease* in damages in other states. Dr. Conti fails to cite or use any peer-reviewed academic literature or scientific sources for either the structural equation or the variable choices made in her GLM regression analysis.[32]

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[31] Conti Report, Attachment E ¶2.

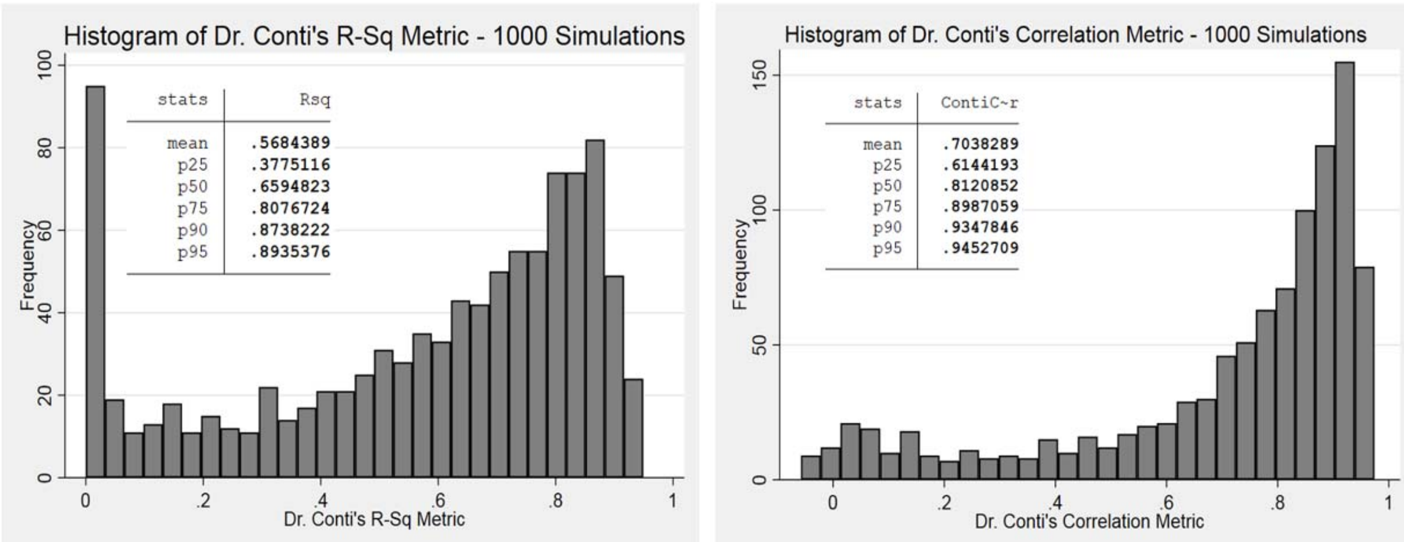
[32] Conti Deposition 282:12-283:1.

a. The results of mixing & matching Dr. Conti's dependent and explanatory variables demonstrate that Dr. Conti's model is a nonsensical and spurious regression

49. To demonstrate the nonsensical and spurious regression that Dr. Conti has created, I randomly mixed and matched her monthly damages for a given state with a different state's "explanatory" variables. For example, I assigned Dr. Conti's monthly damages for California to the explanatory variables of Washington, D.C. This mismatched assignment of state variables was then performed for all the remaining 14 states. I then ran Dr. Conti's GLM regression model on these mismatched state assignments, which should result in poor regression results if the model is theoretically sound. In other words, if Dr. Conti's set of explanatory variables were, in fact, meaningful and causal, then we would expect these randomly "mixed and matched" models to perform poorly, by even Dr. Conti's own standards.

50. After simulating one thousand sets of mixing and matching the 14 states' dependent and explanatory variables and running Dr. Conti's GLM regression model, I find that the randomly "mixed and matched" models do not perform poorly. To the contrary, these theoretically nonsensical regressions perform nearly as well and often better than Dr. Conti's GLM regression model, which confirms that Dr. Conti's set of explanatory variables are not meaningful and causal. The figure below shows that half of all random mix and match assignments achieve a correlation of 0.812 (i.e., 0.659 R-square) or better, with approximately 5% of simulations achieving a correlation result that is the same or better than that of Dr. Conti's model, 0.941 (i.e., 0.886 R-square).

Figure 13



51. A reliable, robust, and theoretically sound regression model would not exhibit these nonsensical results. These results clearly demonstrate that Dr. Conti's regression and extrapolation methodology is deficient, and any results from such a method are misleading and unreliable.

b. Dr. Conti's regression results flip-flop when her regressions are performed on individual states

52. If Dr. Conti's regression model were actually measuring a causal relationship between her alleged damages and her explanatory variables, then we would expect there to be relatively stable and consistent regression results across each of the states. For example, Dr. Conti uses the total population of a state as one of her explanatory variables. One might expect that an *increase* in the population for a given state would *increase* Dr. Conti's alleged damages. If there were indeed a causal relationship between Dr. Conti's damages within a state and a state's population size, then Dr. Conti presents no reasons as to why this relationship would

substantially differ depending on which state was being analyzed. As I show below, this is true for almost all of the other explanatory variables in Dr. Conti's GLM regression model.

53. When Dr. Conti's regression model is run separately for each state, I observe that the relationship between her damages and her explanatory variables flip-flop from being *positively* related to damages in one state to being *negatively* related to damages in another state.[33] For example, there is a *negative* relationship between the state's population and damages for AZ / CA / DC / IN / MA / NJ / NY and OH; however, there is a *positive* relationship between population and damages for the overall model, FL / GA / IL / MD / PA and TX. Additionally, the magnitude of these flip-flopping relationships drastically changes from state to state with the positive relationship between damages and state population in DC being 630 times that of CA, or the negative relationship between damages and state population in IL being 34 times that of TX. These results are not supported by any economic theory and highlight how Dr. Conti's GLM model is deficient.

54. The table below summarizes how Dr. Conti's regression results flip-flop from state to state, variable by variable. The colors in the table denote whether Dr. Conti's regression model measured a *positive (Blue)* or *negative (Orange)* relationship between damages and the given explanatory variable. The numeric values in the table's cells are the regression model coefficients or betas, and measure the non-linear relationship between the damages and the given explanatory variable. The key visual finding from the table is the flip-flopping of the relationship between Dr. Conti's damages and explanatory variables from one state to the next.

[33] When Dr. Conti's GLM regression model is run on each state separately, I remove the state-specific demographic variables for age and male percentage of the population (i.e., I removed all the demographic percentage variables). This is done to allow Dr. Conti's model to be run on each state separately.

For example, total population and damages are *positively (Blue)* related to damages for the overall models and flip to being *negatively (Orange)* related to damages for AZ / CA / DC and flip back again to being *positively* related to damages for FL / GA / IL, etc.

Figure 14

	Dr. Conti Regression Result	Dr. Conti Regression Result Without %Age and %Male Vars	Dr. Conti Regression Result Without %Age and %Male Vars By State													
VARIABLES	Overall damages	Overall damages	AZ damages	CA damages	DC damages	FL damages	GA damages	IL damages	IN damages	MA damages	MD damages	NJ damages	NY damages	OH damages	PA damages	TX damages
uspharsales	-54.17	22.38	16.88	7.71	-100.1	-45.99	39.17	-23.44	6.882	16.06	3.647	-31.81	-67.52	11.12	55.51	-53.12
total_population	0.116	0.0428	-3.502	-0.624	-3.256	0.208	1.317	13.36	-2.539	-2.866	0.644	-7.866	-1.162	-26.4	6.399	0.371
medinc_m	0.0247	-0.0172	-0.00575	0.155	0.0289	-0.00189	-0.0942	-0.0041	0.0118	0.0378	0.00357	0.0935	-0.00101	0.202	0.0634	-0.00809
pctinscov_m	0.0619	0.0736	0.428	-0.0832	0.148	0.14	0.103	0.0529	0.0185	0.0227	-0.0636	-0.0267	0.0829	-0.33	-0.0513	0.0841
tot_med_dol	9.56E-03	-0.00218	0.00111	0.0151	-0.0259	-0.00601	-0.0265	-0.0133	0.36	-0.204	-0.254	0.035	0.0471	-0.0455	-0.0484	0.117
lcvspc	1.211	1.146	0.658	6.878	2.221	-0.57	1.172	-4.32	22.14	-1.642	13.97	14.39	8.536	12.09	-12.78	-2.681
2.month	0.555	0.637	0.511	0.835	0.804	0.698	0.852	0.311	0.633	0.518	0.282	0.501	0.545	0.572	0.625	0.643
3.month	0.92	0.889	0.768	1.104	1.303	1.077	1.082	0.635	0.825	0.733	0.581	0.849	0.913	0.818	0.809	0.966
4.month	1.023	1.041	0.916	1.205	1.385	1.154	1.242	0.811	1.02	0.731	0.776	1.01	1.074	0.916	1.072	1.152
5.month	1.02	1.03	0.891	1.143	1.35	1.076	1.266	0.868	0.973	0.745	0.761	0.968	1.088	0.903	1.09	1.174
6.month	1.013	1.07	0.88	1.161	1.325	1.043	1.323	0.931	1.009	0.74	0.782	0.914	1.092	0.91	1.167	1.199
7.month	1.046	1.1	0.922	1.154	1.285	1.082	1.374	0.909	1.043	0.7	0.819	0.968	1.134	0.911	1.232	1.29
8.month	1.097	1.123	0.912	1.162	1.316	1.11	1.417	0.978	1.076	0.708	0.794	0.914	1.145	0.848	1.262	1.348
9.month	1.096	1.152	0.942	1.185	1.306	1.124	1.461	0.983	1.114	0.695	0.808	0.907	1.142	0.833	1.298	1.326

55. To further support the finding that Dr. Conti's model lacks robustness and reliability, I performed two cross-validation tests.[34] The first test was to run Dr. Conti's identical regression dropping one state at a time and measuring the percent difference in total predicted damages for the 14 states. The second test was to drop one year at a time and to again measure the percent difference in total predicted damages for the 14 states. These cross-validation tests demonstrate an unreliable and unstable model that cannot be used for extrapolation purposes. The cross-validation by state shows that dropping one state (and still predicting damages on this state) changed Dr. Conti's total damage predictions by -21% to +11%. The cross-validation by

[34] Deb, P., Norton, E., Manning, W. (2017). *Health Econometrics Using Stata*. Stata Press, pp. 20-21.

year shows that dropping one year (and still predicting damages on this year) changed Dr. Conti's total damage predictions by -13% to +4%.

v. Dr. Conti's claims of her model "doing well at predicting damages within the 14 states" is misleading and unfounded

56. Dr. Conti states multiple times in her report[35] [36] and in her deposition[37] that her regression model is "doing well at predicting damages *within* the 14 states with CVS data" (emphasis added), and she presents a misleading set of charts[38] detailing her regression model's fit for the 14 states. A closer and more revealing, review (which I provide directly below) of Dr. Conti's own charts from her Figure 1 in her Attachment E demonstrates that her model does not "do well" at predicting damages within the 14 states with CVS data. This fair and accurate review also reveals that her charts show a model with systemic biases and unreliable predictions.

57. Dr. Conti presents a set of 14 charts, one for each of the 14 states with CVS data, that is highly misleading. All of her 14 small charts in Figure 1 in her Attachment E use the same y-axis for total damages that start at $0 and end at $4 million, forcing smaller states to use the same axis as larger states such as MA, CA, and NY. I have generated a separate chart for each state with an appropriate y-axis to allow us to see how poorly Dr. Conti's model performs across the 14 states with CVS data. These 14 separate charts of Dr. Conti's Attachment E Figure 1 are in my Appendix D, and I present three of them below.

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[35] Conti Report ¶79.

[36] Conti Report, Attachment E, ¶5.

[37] Conti Deposition 276:11-12.

[38] Conti Report, Attachment E, Figure 1.

Figure 15

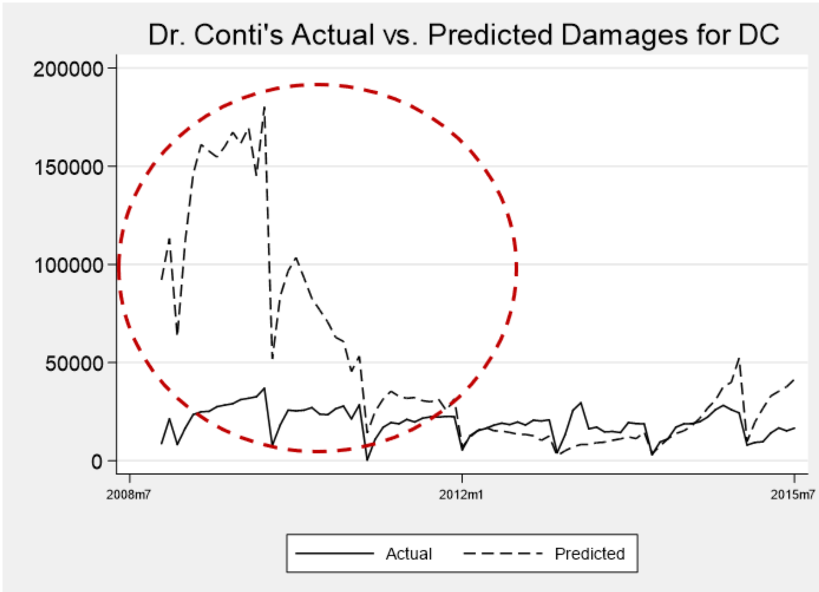


Figure 16

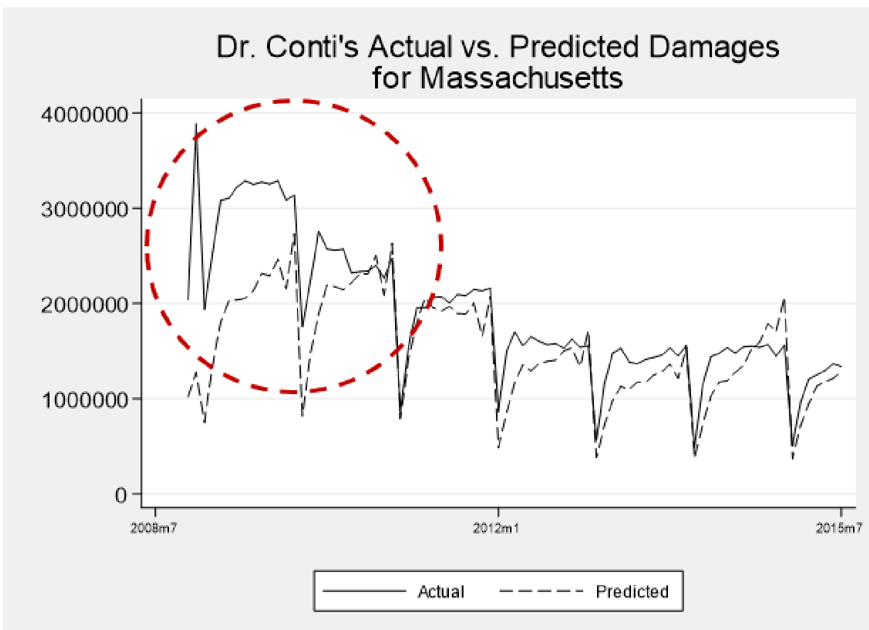
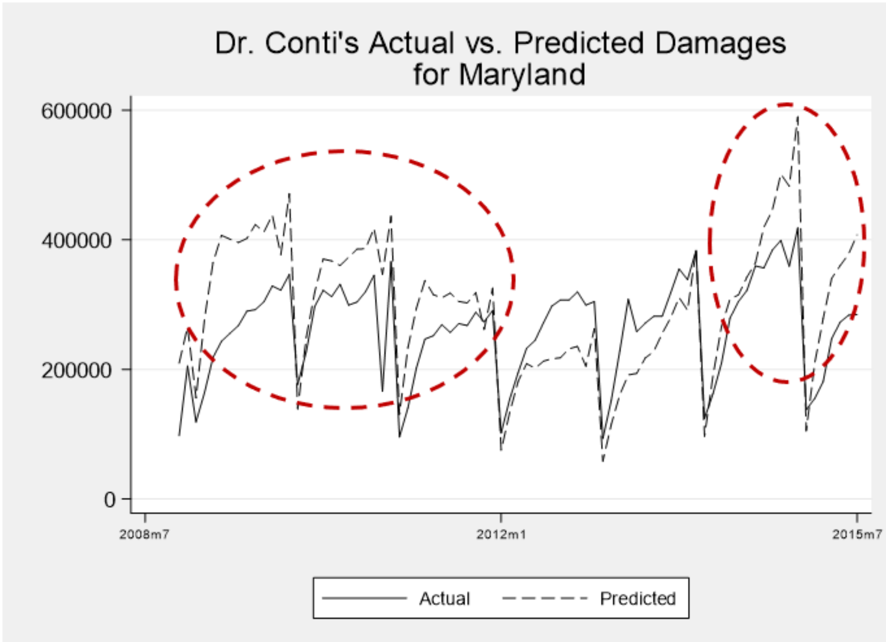


Figure 17



58. Dr. Conti's model exhibits systemic errors and unreliable damage predictions once we appropriately present her Attachment E Figure 1 charts without her misleading scales along the y-axis. We can now observe entire periods where the model is systemically over or under predicting damages, states where the model is consistently biased upward or downward, and visible regime changes in the model's prediction accuracy.

59. In this context, a regime change is when the relevant correlations measured by the GLM model systematically change over time and cause systematic overpredictions or underpredictions of damages. This concept of Dr. Conti's GLM model fundamentally changing over time from one time period to the next is often known as a structural break or regime

change,[39] a term that Dr. Conti appeared unaware of at her deposition.[40] I performed a series of statistical tests, known as Chow Tests, and find that Dr. Conti's model does systemically change over time and by state.[41]

60. All of these features are indicative of a misspecified model whose predictions and extrapolations are unreliable and misleading.

a. Dr. Conti paradoxically claims her model "performs well" within the 14 states with CVS data in her report, however, disavows having looked at her model's prediction by states in her deposition

61. Dr. Conti's report claims that her model is "doing well at predicting damages *within* the 14 states with CVS data" (emphasis added) and presents detailed state by state monthly damages tables in Attachment C and misleading state by state fit charts in Figure 1 of Attachment E of her report. However, when questioned about her model's performance at the state level, Dr. Conti admits that she did not look at specific states.[42]

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[39] Guajarati, D. (2004). *Basic Econometrics, (4th Ed.)*. McGraw-Hill, p. 273.

[40] Conti Deposition 277:13-22.

[41] See Stata working papers for regime change (Chow Test) results for a 2012 breakpoint for time and a regime that consists of states whose postal codes precede "MA" in alphabetical order.

[42] Conti Deposition 278:4-12.

A For the 14 states where I have data?
Q Yes.
A Yes.
Q And so you are aware of it. What is the answer? Does it change significantly based on which state you're looking at?
A So the explanation of how the model predicts or doesn't within state over time is provided in my report. And I haven't looked specifically at individual states, but it's knowable with the data that I have and the method I've provided.
Q Before submitting your report, did you test any of the independent variables that you used in your GLM for skewness or kurtosis?
A Any of -- can you restate, please?
Q Before submitting your report, did you test any of the independent variables used in your GLM for skewness or kurtosis?
A Let's look at the appendix, shall we, where we discuss this? Or the attachment.
Q And I can direct you to paragraph 4.
A Oh, you have a specific question or paragraph in mind?
Q Well, I'll -- just for --

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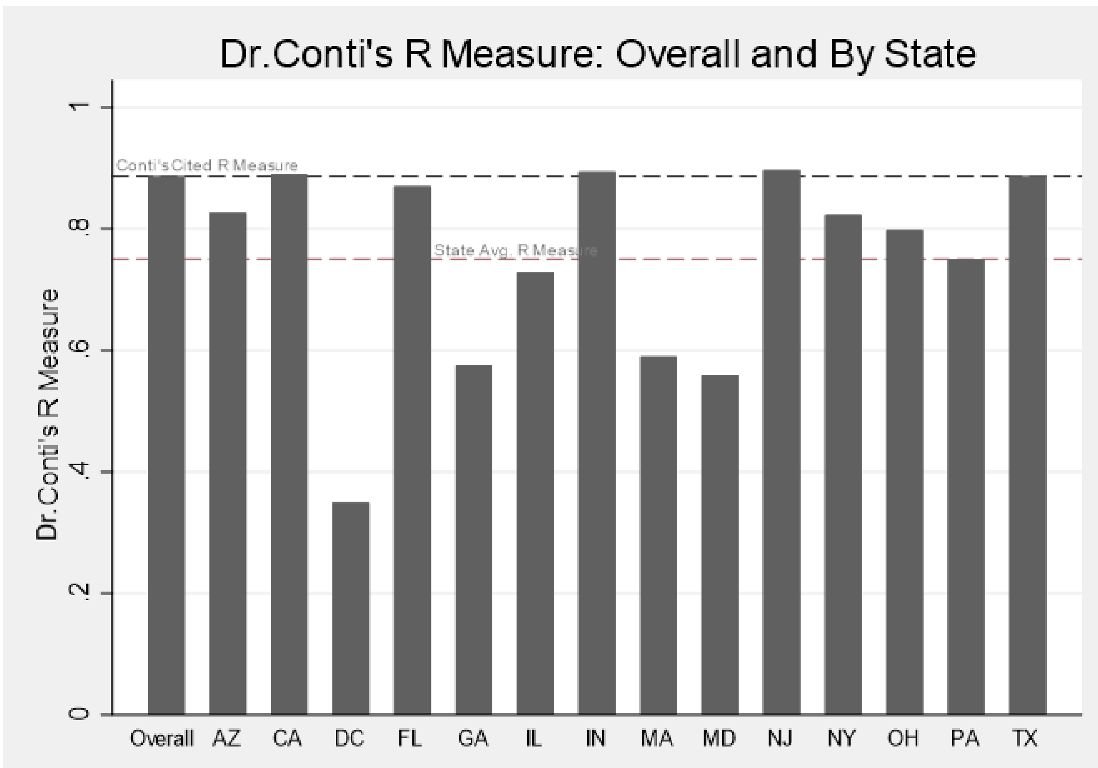
62. Dr. Conti has failed to consider, assess, or demonstrate her model's prediction accuracy and reliability by state, when in fact, she uses her model to predict or extrapolate damages to the other 36 states, *by individual state.* Dr. Conti did not create an aggregate 14-state model, she created a 14-individual-state model, with individual-state predictions. She then attempts to extrapolate her 14-individual-state to 36 out-of-sample states, not aggregately, but also state by state. A review of Dr. Conti's model's state-level performance is critical to assessing how the model performs at predicting damages on the 36 states for which she has no CVS pharmacy data.

63. Dr. Conti claims that her model is "doing well at predicting damages *within* the 14 states with CVS data" (emphasis added). In an attempt to support this claim, she cites the correlation between actual and predicted damages of 0.941 and corresponding R-square measure

of 0.886.[43] These two metrics are calculated using the overall regression results, but Dr. Conti fails to report out these two metrics by state. If she had done so, similar to her damages tables and Figure 1, we would have observed R-square metrics by state that are far below the .886 that Dr. Conti reports.

Figure 18



64. The chart above shows how Dr. Conti's overall R-square metrics hide her model's actual poor performance by state. For example, DC has an R-square measure of less than 0.4, and MA, GA, MD are all below 0.6.

[43] Conti Report, ¶79 and Attachment E ¶5.

VI. CONCLUSION AND SUMMARY OF OPINIONS

65. Based on my review of the Conti Report, Dr. Conti's deposition transcript, the CVS data provided to me by counsel, and the demographic data and computer scripts provided from Dr. Conti, I have the following opinions.

66. It is my opinion the Dr. Conti's proposed methodology to calculate out-of-pocket losses (in the 14 states for which she has CVS data) for the proposed class of TPPs using the CVS Reimbursement Data is deficient, and its results are unreliable.

67. Further, it is my opinion that even if Dr. Conti were able to calculate reliable damages in the 14 states mentioned above, the statistical model used by Dr. Conti to calculate out-of-pocket losses for the proposed class of TPPs (in the 36 states for which she does not have CVS data) is fatally flawed, and its results are misleading and unreliable.

Submitted on July 16, 2019

Michael Salve, Ph.D.

APPENDIX A

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Michael Salve is a Senior Managing Director in FTI Consulting's Economic Consulting Services practice based in New York City.

Dr. Salve is an applied economist with experience in advanced quantitative methods, statistical studies, healthcare claims sampling, False Claims Act matters, econometric modeling, CMS, MAC, RAC and ZPIC audits, network analysis and commercial disputes.

He holds a doctorate in economics, with concentrations in both applied econometric and statistical techniques and industrial organization. He currently serves as an adjunct faculty member at Hunter College in New York City where he teaches Econometrics, and Law and Economics in the graduate economics program.

Dr. Salve has extensive experience in designing statistical samples, developing complex extrapolation and benchmarking models, and evaluating achieved precision levels for clients in the healthcare industry. He also uses network analysis to reveal unexpected, yet systematic, relationships among admitting physicians, tending physicians and other providers with respect to their common billing and claim submission patterns.

He also testifies on the use of econometric and statistical models for estimating exposure and potential damages for healthcare clients in litigation. Results of his statistical work have been presented to the SEC and DOJ. He has presented testimony in federal court in a qui tam false claims act matter and has also been deposed by the US DOJ and has been cross examined by the New York State Office of the Medicaid Inspector General.

He has constructed sampling techniques used to develop statistically reliable results for inclusion in expert testimony. Specifically, he has assisted healthcare clients and lending institutions in areas such as addressing allegations of fraudulent or improper billing practices and quantifying financial accuracy measures.

Dr. Salve has successfully worked with teams of professionals from engaging law firms on issues relating to relevant data requests during the discovery period, proper extrapolation methodologies to unknown populations and identification of potential bias in existing samples.

Prior to joining FTI Consulting, Dr. Salve was a Principal with the Forensic and Dispute Services Group of a Big Four Accounting Firm, where he led the Economic Consulting Services practice in New York and was a Managing Director at a private consulting firm where he led the statistical sampling work in the US. He has been a teaching fellow and graduate mathematics instructor at Boston College and was an adjunct faculty member at Suffolk University.

Professional Experience

Statistical Analyses and Sampling Procedures for Healthcare Litigation

Qui Tam / False Claims Act Litigation- Retained multiple times as the statistical sampling and damages expert. Responsible for working with independent coding experts to provide a rebuttal damages claim regarding alleged overpayments from Medicare/Medicaid. Statistical work is closely aligned with the guidelines of the U.S. Department of Health and Human Services, Centers for Medicare and Medicaid Services Medicare Program Integrity Manual to ensure all sampling procedures and extrapolation methodologies are appropriate. Econometric analyses have included survivor models that test whether temporary admission programs have led to inappropriate hospice care patient admissions.

Healthcare Claims Audit- Served as the statistical expert to assist a TPA in evaluating potential exposure from overpaid claims. Statistical sampling was used to determine overpayment exposure in three different strata: medical, surgical and VA services. Statistical sampling guidelines from the U.S. Department of Health and Human Services were used to ensure consistency with industry standards.

ZPIC Audit of Medicare/Medicaid Reimbursement- Served as the statistical sampling expert for several healthcare facilities in defense of ZPIC audits. Role was to address potential deficiencies in the ZPIC's sampling plan and extrapolation methodology.

Medicare/Medicaid Reimbursement Litigation- Served as the statistical sampling expert in a large healthcare litigation matter. Specifically, a healthcare provider extrapolated sample "underpayments" to the entire population of claims for a total "underpayment" amount. Statistical role was to examine plaintiff's damage analysis and the extrapolation methodology.

Insurance Coverage Dispute- Retained as economic expert witness to perform statistical extrapolation of quantitative results from FDA clinical trials to the entire population of patients taking particular prescription medications. Statistical analysis involves several medications over several years with many different clinical trial results.

Publications/Presentations

- "Health Care Data Analytics: Visualizing Complexity and the Unexpected" New England Healthcare Internal Auditors Annual Compliance & Audit Conference, Mystic, CT, November 2016.
- "Health Care Data Analytics: Fraud Detection, Audits & Network Analysis" Health Care Compliance Association, New York, New York, May 2016.
- "Healthcare Audit Sampling & Analytics", Healthcare Financial Management Association, Jericho, New York, October 2015.
- "Intellectual Property Disputes – Assessment of Dispute Damages", Electronics Intellectual Property, Beijing, April 2015.
- "Intellectual Property Disputes – The Application/Role of Quantum Experts and Assessment of Dispute Damages", Electronics Intellectual Property, Beijing, June 2014.
- "Data Analytics and Infographics Used In Detecting Illicit Behavior", A&M Professional Spotlight, 2014.
- "Intellectual Property Loss Quantification in Asia," Presentation to King & Wood Malleson's attorneys, February 2014, Beijing
- "Intellectual Property Loss Quantification and Valuation," Presentation to Herbert Smith attorneys, January 2013, Shanghai
- "The Role of the Expert Witness in Arbitration," Presentation to Zhong Lun attorneys, January 2013, Shanghai
- "Intellectual Property Loss Quantification and Valuation," Presentation to Jun He attorneys, January 2013, Shanghai
- "Quantum Aspects of Intellectual Property Cases in International Arbitration," Presentation at China International Economic and Trade Arbitration Commission, Shanghai Commission, January 2013, Shanghai
- "Intellectual Property Loss Quantification and Valuation," International presentation to Hogan Lovells attorneys, March 2009, Hong Kong
- "The Securitization of Stranded Assets," The Business Council of Southwestern Connecticut (SACIA), March 1998, Stamford, CT
- "Electric Utility Restructuring in the U.S.," Economics and Finance Departments of the University of Pamplona, June 1997, Pamplona, Spain
- "Methodologies of Forecasting Electricity

Demand Used in the U.S.," International Conference, PowerGen '97, June 1997, Madrid, Spain

- "How Retail Customers Benefit from Real-Time Pricing," National Rural Electric Cooperative Association's 1996 G&T Update, Fall 1996 Indianapolis, IN
- "The Potential for Predatory Behavior in the Electric Utility Industry Stemming from the CAAA90," Allied Social Science Association Meetings, January 1996, San Francisco, CA
- "Market Power and the EPA's Acid Rain Program," Western Economic Association Meeting, June 1994, Vancouver, B.C.

Expert Witness Testimony in the Last Five Years

- Deposition testimony in the litigation between Laurie Freeman, *et al*.,v. Grain Processing Corporation, Case No. KACV921232. Iowa District Court for Muscatine County (2018).
- Hearing testimony in the litigation between Mark D. Kleinsasser v. Progressive Direct Insurance Company and Progressive Max Insurance Company, Case No. 17-cv-05499. United States District Western District of Washington at Tacoma (2018).
- Deposition testimony in the litigation between Lorena Armijo, *et al*.,v. ILWU-PMA Welfare Plan, *et al*, Case No. 2:15-cv-1403-MWF-VBK. United States District Court Central District of California (2017).
- Deposition testimony in the litigation between Christopher Corcoran, et al v. CVS Pharmacy, Inc., Case No.: No. 15–CV–03504–YGR. United States District Court Northern District of California Oakland Division (2017).
- Hearing testimony in the litigation between Buffalo Emergency Associates, LLP v. HealthNow New York, Inc. (d/b/a Blue Cross Blue Shield of Western New York), Case No.: 3393. American Health Lawyers Association, ADR Service, New York State (2017).
- Deposition testimony in the litigation between Naturalock Solutions, LLC v. Baxter Healthcare Corporation, *et al*, Case No.: 1-14-cv-10113. United States District Court for the Northern District of Illinois (2017).
- Deposition testimony in the litigation between Buffalo Emergency Associates, LLP v. HealthNow New York, Inc. (d/b/a Blue Cross Blue Shield of Western New York), Case No.: 2812. American Health Lawyers Association, ADR Service, New York State (2017).
- Deposition testimony in the litigation between the State of West Virginia v. AmerisourceBergen Drug Corporation, *et al*, Case No.: 12-C-141. Circuit Court of Boone County, West Virginia (2016).
- Deposition testimony in the litigation between Portfolio Recovery Associates, LLC v. Caroline L. Houston and Caroline L. Houston (and others similarly situated) v. Portfolio Recovery Associates, LLC, Case No.: 12-CVS-642. General Court of Justice, Superior Court Division, North Carolina, Iredell County (2016).
- Deposition testimony in the litigation between Musashi, L.L.C. and Huff Asset Management Co., L.L.C. vs. Virgin Media, Inc., Civil Action Docket No.: MRS-L-734-13. Superior Court of New Jersey, Morris County: Law Division (2016).
- Trial testimony in the litigation between Lendingtools.com Inc. vs. Bankers Bank of Kansas, N.A. and The Banker's Bank, N.A., Case No. 11CV1879. Eighteenth Judicial Sedgwick District Court, Kansas (2016).
- Deposition testimony in the litigation between United States of America, *ex rel*. Misty Wall vs. Vista Hospice Care, Inc. d/b/a VistaCare; VistaCare, Inc., and Odyssey Healthcare, Inc., Civil Action No. 3-07-CV-0604-M. United States District Court for the Northern District of Texas (2016).
- Deposition testimony in the litigation between Gene Achziger vs. IDS Property Casualty Insurance Company, Case No. 3:14-cv-05445-BHS. United States District Court, Western District of Washington at Tacoma, Washington (2015).
- Deposition testimony in the litigation between Lendingtools.com Inc. vs. Bankers Bank of Kansas, N.A. and The Banker's Bank, N.A., Case No. 11CV1879. Eighteenth Judicial Sedgwick District Court, Kansas (2015).
- Testimony in the litigation between United States of America, *ex rel.* Cecilia Guardiola v. Renown Health, Renown Regional Medical Center, and Renown South Meadows Medical Center, Case No. 3:12-cv-00295-LRH-VPC. United States District Court for the District of Nevada (2014).
- Deposition testimony in the litigation between SMS-THL Holdings I, Inc. v. James Kleeman, *et al*, Case No. CV 2012-013360. Arizona Superior Court, Maricopa County (2014).

Teaching Experience

- Adjunct Faculty, Hunter College, 2011 to Present (Law and Economics, Econometrics)
- Teaching Fellow, Boston College, 1994 to 1995 (Statistics, Macroeconomic Theory)
- Adjunct Faculty, Suffolk University, 1993 to 1994 (Microeconomic Theory)
- Graduate Mathematics Instructor, Boston College, 1993 to 1995 (Calculus, Linear Algebra)

Recognition

- H. Michael Mann Teaching Award, Boston College, 1994

Employment History

- FTI Consulting, Senior Managing Director (February 2015 to present)
- Alvarez & Marsal, Managing Director, (December 2008 to February 2015)
- Deloitte Financial Advisory Services, Principal (May 2000 to November 2008)
- KPMG, Manager (January 1997 to May 2000)

APPENDIX B

Appendix B
Materials Reviewed

<u>Pleadings / Complaint</u>
2018.05.04 - 81 - Amended Complaint.pdf
2-Memo ISO Motion for Class Certification [FILED UNDER SEAL].pdf

<u>Data Files</u>
DCVS – 00000000001 through DCVS – 01003855926
5.19.17 - List of CVS Retail Pharmacies Nov 2008 to Feb 2016.xlsx
6.20.17 - Additional List of CVS Retail Pharmacies.xlsx
Age, Sex, Race, by state, 2010-2016.csv
CVSSM-0025726.xlsx
ESI0000001 (HIGHLY CONFIDENTIAL - ATTORNEYS' EYES ONLY).xlsx
H08.xls
KFF_State_Insurance_Coverage.xlsx
MedianRealHouseholdIncomes2008_2016.csv
mpop (access date 04 19 2019).dta
MRTSSM44611USN (access date 04 18 2019).csv
SMW_RECAP_20180718.txt
SMW_RXCLAIMS_20180718.txt
State_Insurance_Coverage.csv
Stconcord.dta
Drug_Utilization_2008_-_All_States.csv
Drug_Utilization_2009_-_All_States.csv
Drug_Utilization_2010_-_All_States.csv
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Drug_Utilization_2012_-_All_States.csv
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01_SAS_DATA_IMPORTS.sas
02_SAS_IN_TEXT_NUMBERS.sas
03_State_Demographic_Data.sas
04_State_CVS_Counts.sas
05_State_CMS_Output.sas
01 CVS Damages - Prep Data.do
02 CVS Damages – Extrapolation.do
CMS_State_Utilization_Monthly.csv
Demographics_2008_2016.csv
Hsp_ndcs_stacked.txt
Pharmacy Counts by State.csv
damages_pred.csv
01_import_csv.claims.sql
02_import_misc.sql
03_Calculate_Damages_Program.sql

<u>Expert Reports / Declarations</u>
004 - Conti_Report_Final [FILED UNDER SEAL].pdf
Conti Materials Relied Upon.pdf

<u>Expert Depositions</u>
RenaConti_COND.pdf

<u>Publicly Available Sources</u>
Deb, P., Norton, E., Manning, W. (2017). *Health Econometrics Using Stata.* Stata Press.
Gujurati, D. (2004). *Basic Econometrics, (4th Ed.)*. McGraw-Hill.
Marcellino, M. (1999). Some Consequences of Temporal Aggregation in Empirical Analysis. *Journal of Business & Economic Statistics*, 17(1).

APPENDIX C

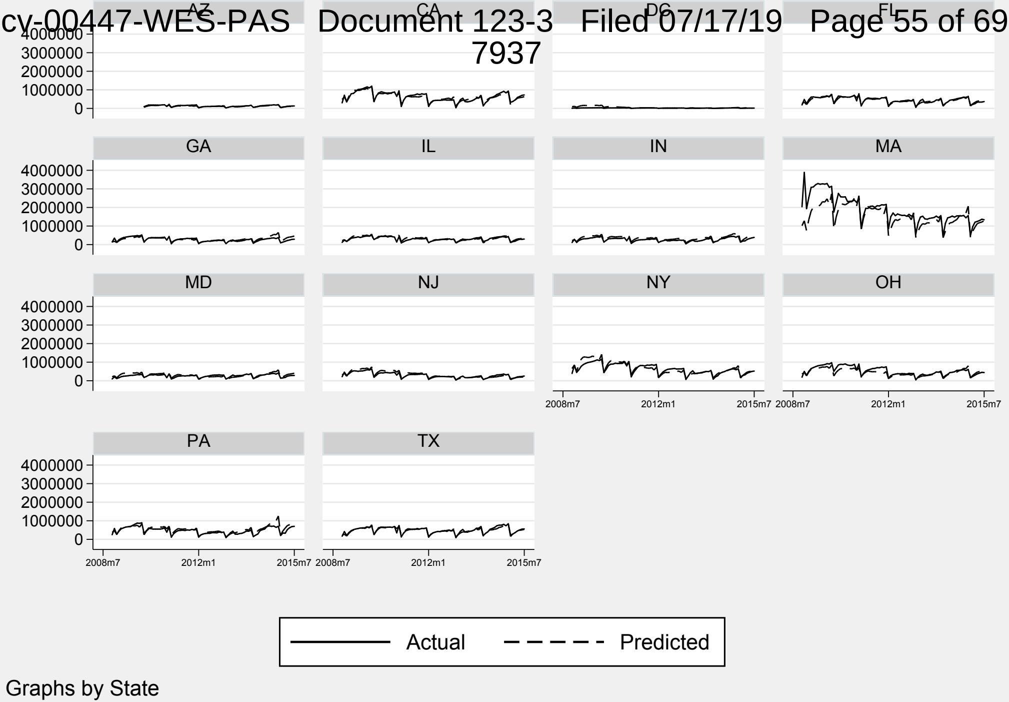
Summary Table

State Name	Average Percent Insured by Month	Average Total Population (in Thousands)	Average Male Population Percent by Month	Average CVS Pharmacy Count per Capita	Average Total Medicaid HSP Dollars (in Millions)	Average Median Income	Average CVS Store Count	Predicted Damages
Rhode Island	57	1,053	0.48	59	$0.36	$54,357	62	$129,773,954
Massachusetts	63	6,643	0.48	56	$1.74	$63,036	371	$123,885,953
Connecticut	61	3,584	0.49	45	$1.42	$67,335	161	$97,398,589
New York	55	19,547	0.48	26	$8.41	$52,067	517	$53,752,896
California	53	37,902	0.50	28	$13.82	$57,494	1,075	$50,286,477
Pennsylvania	59	12,745	0.49	35	$3.82	$52,545	447	$44,093,876
Utah	65	2,844	0.50	5	$0.38	$60,233	15	$40,592,531
Texas	50	25,960	0.50	27	$5.80	$51,298	700	$39,567,759
Florida	46	19,305	0.49	44	$4.14	$46,246	842	$36,819,511
Ohio	57	11,558	0.49	33	$3.60	$47,162	377	$36,545,807
Indiana	57	6,532	0.49	52	$1.62	$47,378	343	$28,371,183
Illinois	58	12,848	0.49	28	$4.70	$54,071	355	$26,674,425
New Jersey	61	8,853	0.49	35	$1.86	$64,594	311	$26,409,737
North Carolina	52	9,716	0.49	37	$2.78	$44,469	356	$25,385,820
Maryland	62	5,865	0.48	36	$1.08	$69,160	212	$24,083,144
South Carolina	50	4,714	0.49	48	$0.84	$43,189	225	$24,048,348
Georgia	52	9,876	0.49	36	$2.58	$47,045	353	$23,557,941
Alabama	52	4,807	0.49	36	$2.29	$42,162	175	$21,429,501
Mississippi	46	2,979	0.49	17	$1.21	$38,197	50	$19,772,839
Michigan	55	9,896	0.49	30	$2.39	$49,453	298	$16,652,161
Arizona	49	6,538	0.50	30	$2.59	$48,629	194	$7,953,157
Missouri	57	6,019	0.49	18	$4.28	$50,894	106	$6,601,169
Kansas	60	2,874	0.50	17	$0.51	$49,531	48	$6,499,224
Delaware	56	914	0.48	11	$0.40	$54,065	10	$6,244,323
Iowa	62	3,073	0.50	11	$0.95	$53,845	33	$5,549,077
Nebraska	62	1,851	0.50	13	$0.38	$54,433	24	$4,714,993
Tennessee	52	6,435	0.49	24	$2.17	$42,561	156	$4,630,575
District of Columbia	58	629	0.47	80	$0.36	$61,370	50	$3,969,176
Virginia	60	8,151	0.49	39	$2.00	$63,340	316	$2,291,004
Louisiana	50	4,585	0.49	25	$2.40	$41,775	115	$2,217,649
Minnesota	64	5,372	0.50	23	$1.69	$60,701	122	$1,864,474
Oklahoma	50	3,807	0.50	16	$1.08	$46,271	61	$985,540
New Mexico	42	2,071	0.49	8	$0.50	$44,002	17	$885,655
Wisconsin	61	5,718	0.50	12	$2.36	$53,641	70	$853,196
New Hampshire	64	1,321	0.49	32	$0.17	$69,265	42	$542,239
Arkansas	47	2,940	0.49	3	$1.16	$40,441	9	$514,703
Idaho	56	1,595	0.50	2	$0.47	$49,434	3	$505,269
Maine	52	1,329	0.49	20	$0.39	$49,553	27	$391,029
Kentucky	52	4,374	0.49	16	$1.94	$41,720	71	$361,406
Oregon	54	3,894	0.49	5	$1.15	$54,145	21	$281,324
Hawaii	59	1,386	0.50	41	$1.90	$61,092	56	$255,741
South Dakota	59	831	0.50	5	$0.13	$50,055	4	$222,495
West Virginia	49	1,851	0.49	29	$1.23	$41,608	54	$142,965
Vermont	54	626	0.49	6	$0.32	$55,819	4	$121,233
Montana	53	1,004	0.50	16	$0.20	$44,816	16	$50,442
Washington	57	6,877	0.50	6	$1.45	$60,287	45	$42,863
Colorado	59	5,176	0.50	9	$1.13	$60,422	47	$28,768
Nevada	54	2,756	0.50	38	$0.43	$49,180	106	$26,637
North Dakota	66	702	0.51	9	$0.10	$54,892	6	$3,748
Alaska	53	723	0.52	4	$0.25	$63,487	3	$1

Average Percent Insured by Month, Average Total Population, Average Male Population Percent by Month, Average CVS Pharmacy Count per Capita, Average Total Medicaid HSP Dollars (in Millions), Average Median Income, Average CVS Store Count and Predicted Damages broken down by State Name.

Source: ContiRegTable_w_Predictions.xlsx

APPENDIX D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2008m7
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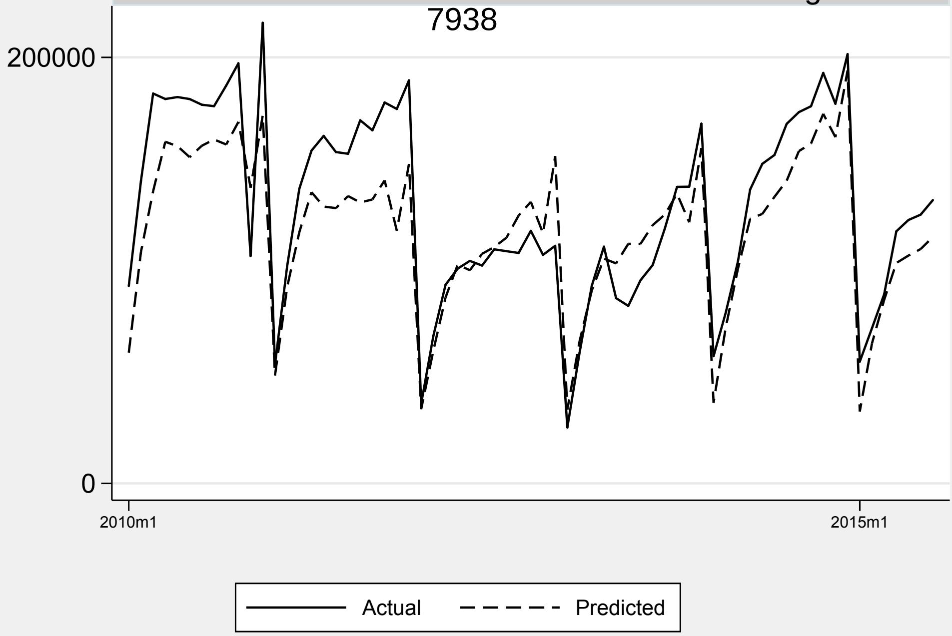
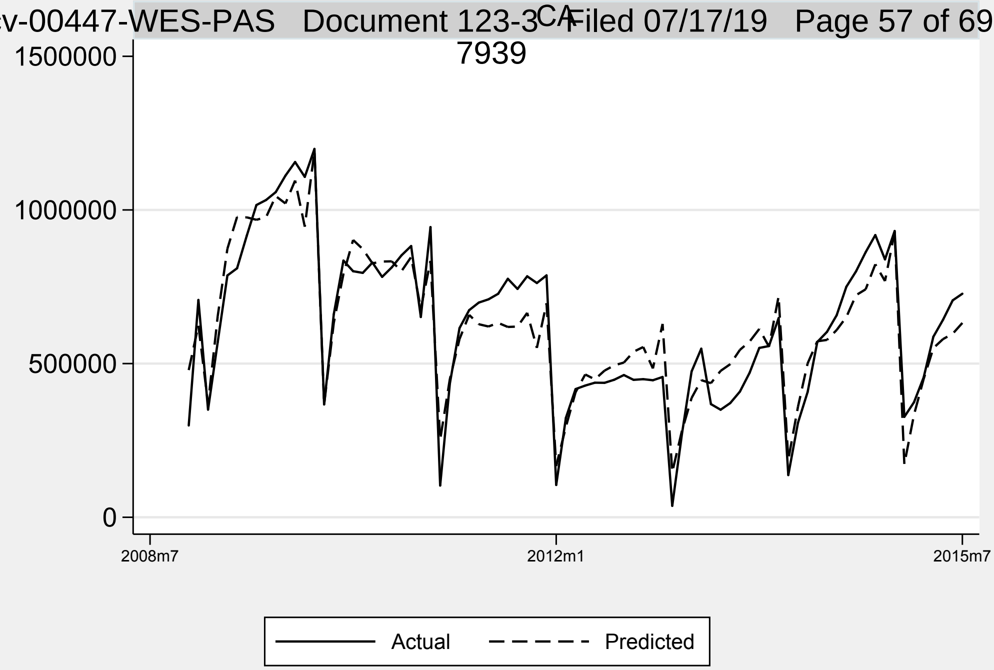
2015m7
Actual
Predicted
Graphs by State

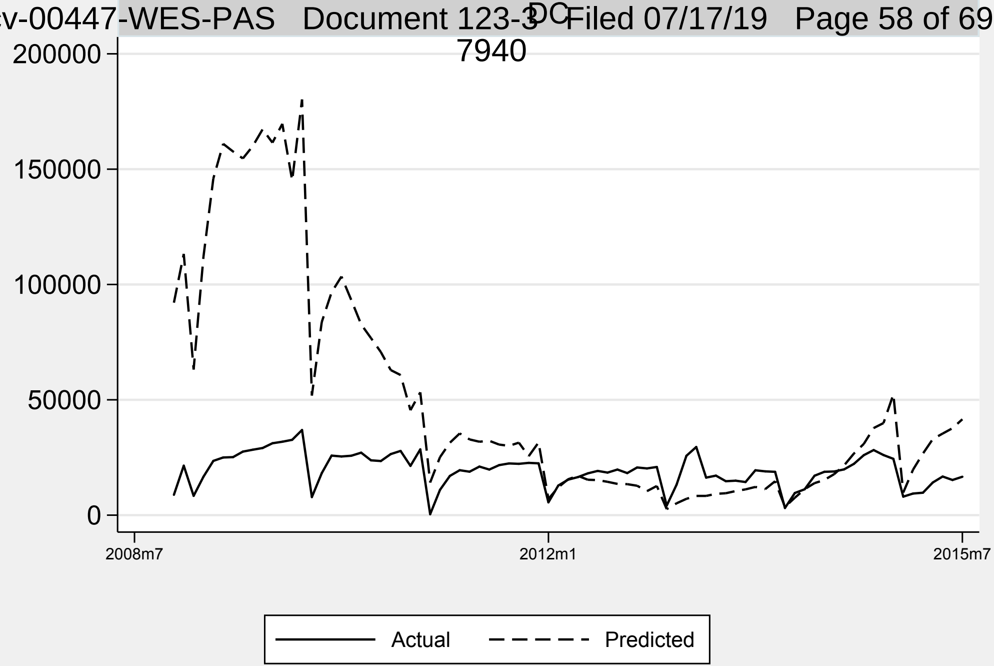
AZ



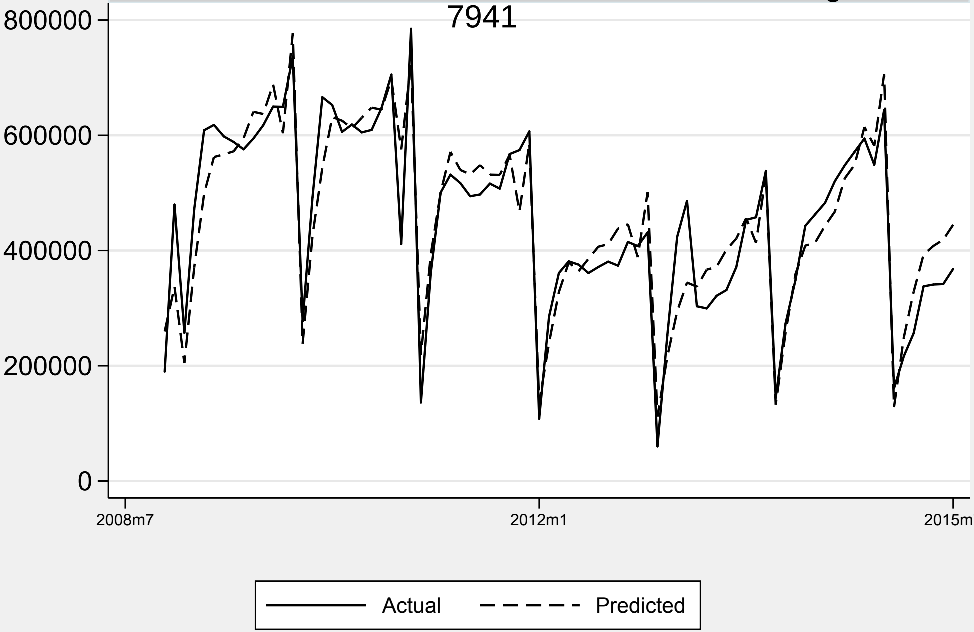
Graphs by State



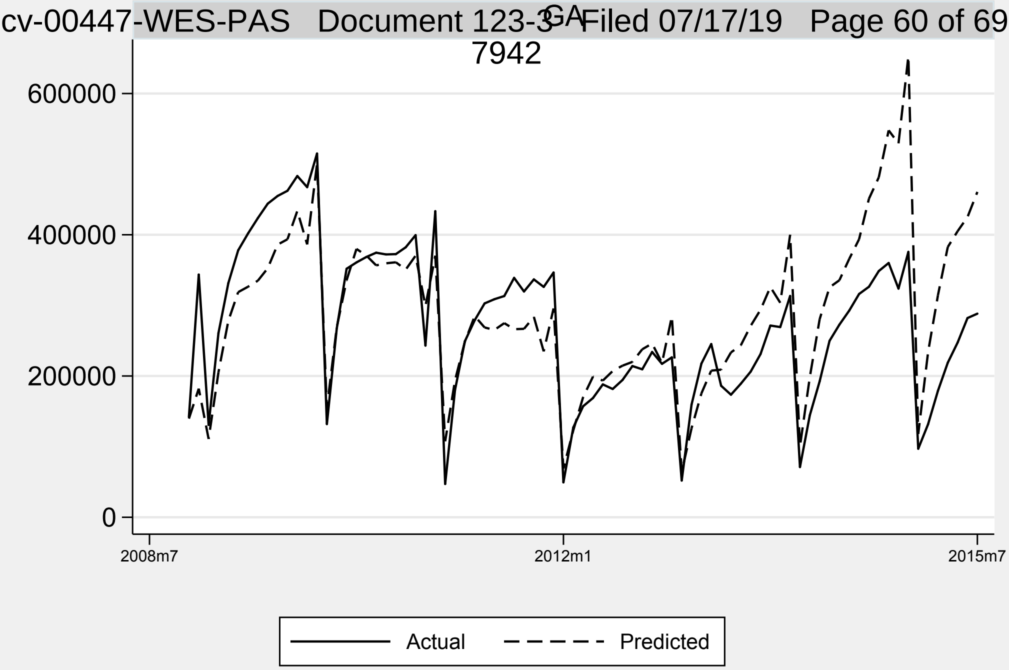
Graphs by State



Graphs by State



Graphs by State



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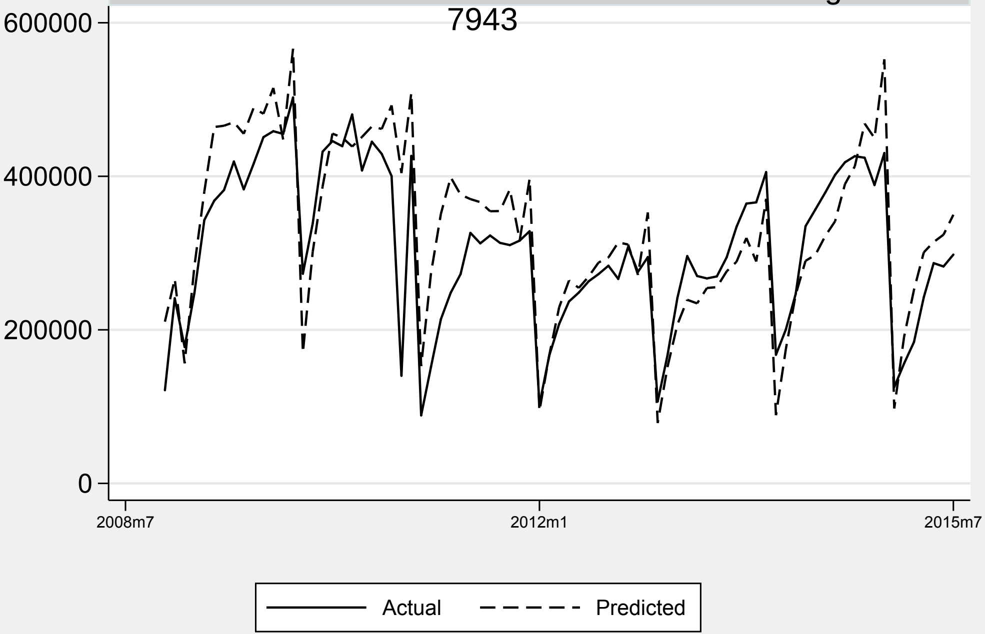
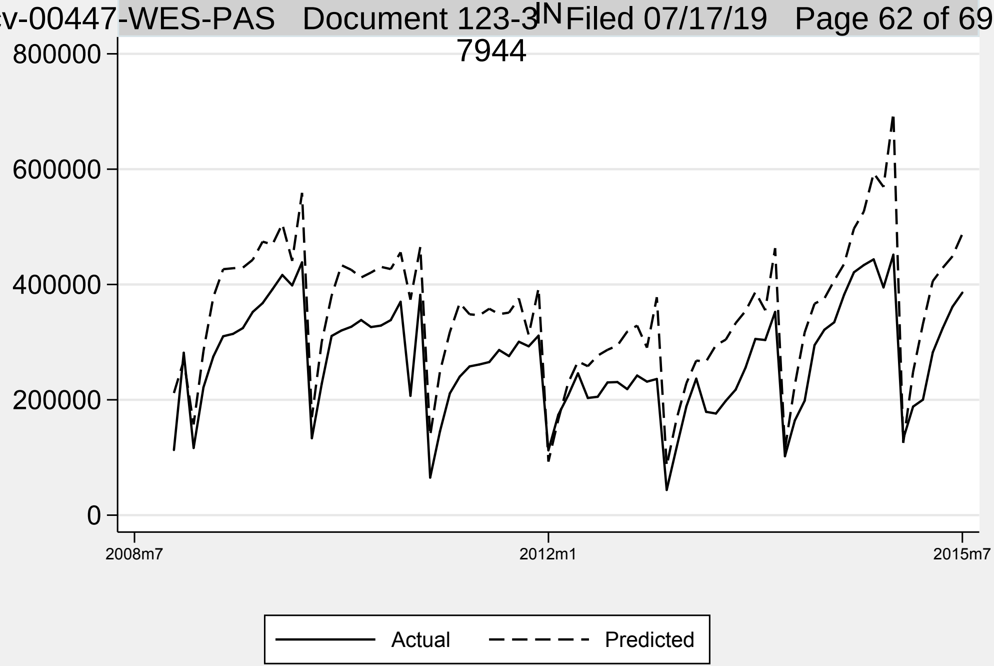
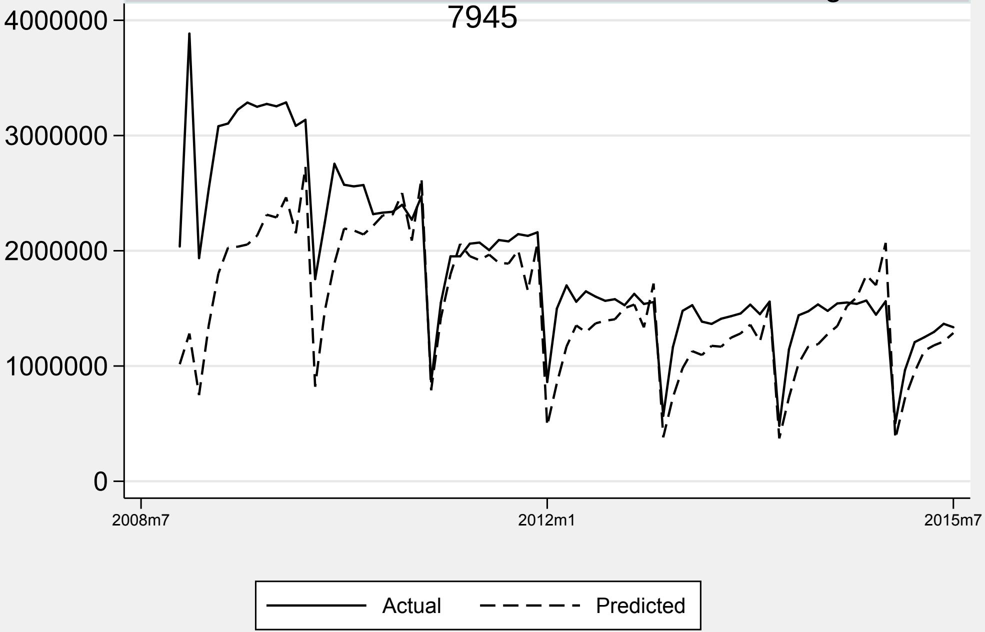


Graphs by State



Graphs by State

MA



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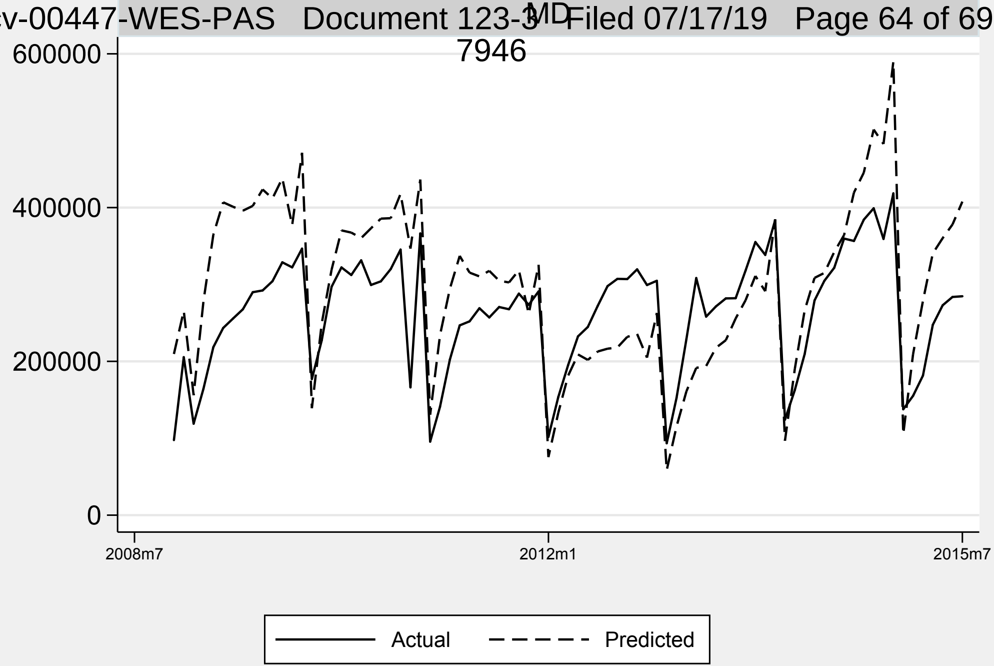

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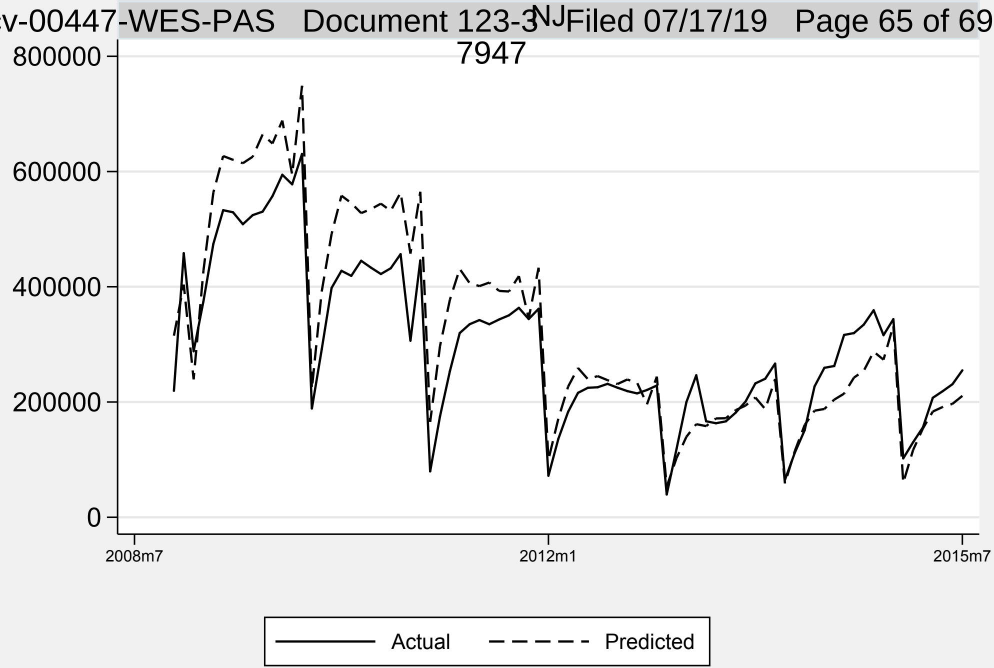

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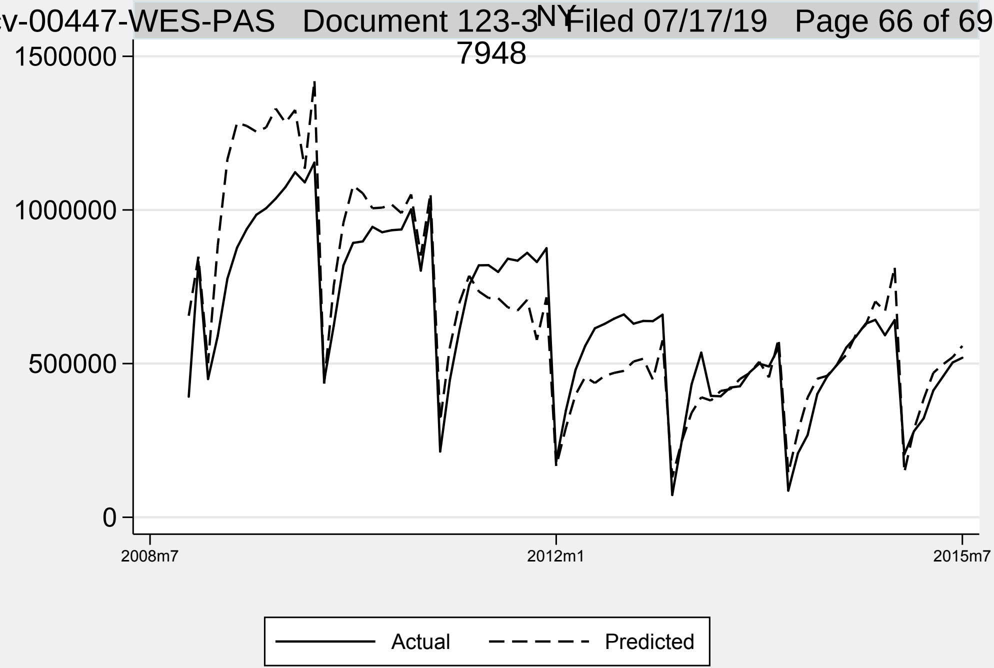

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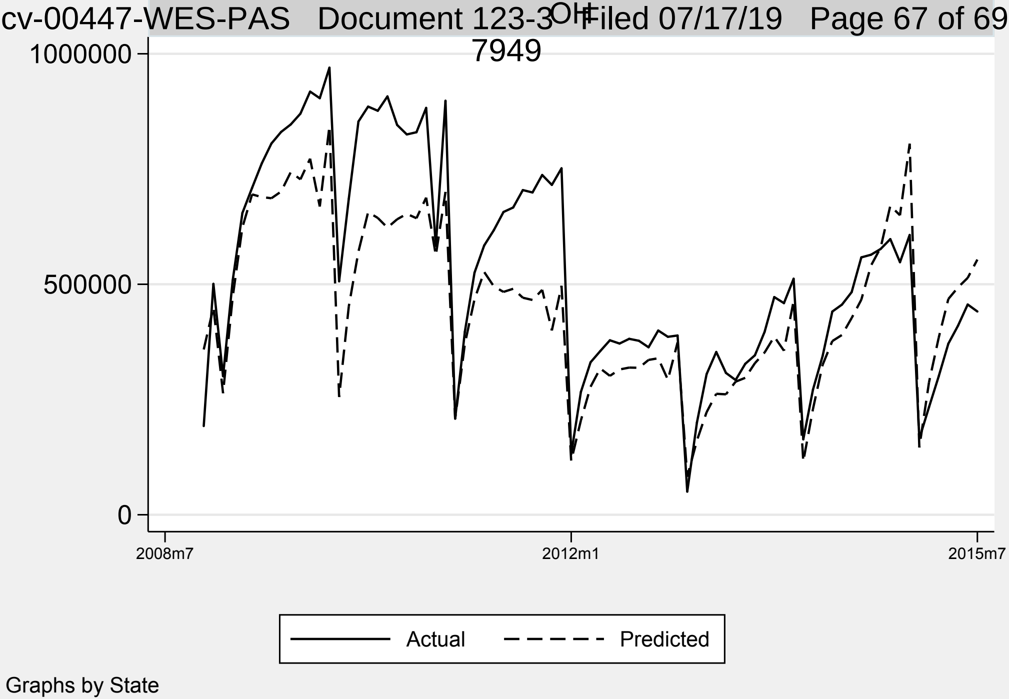
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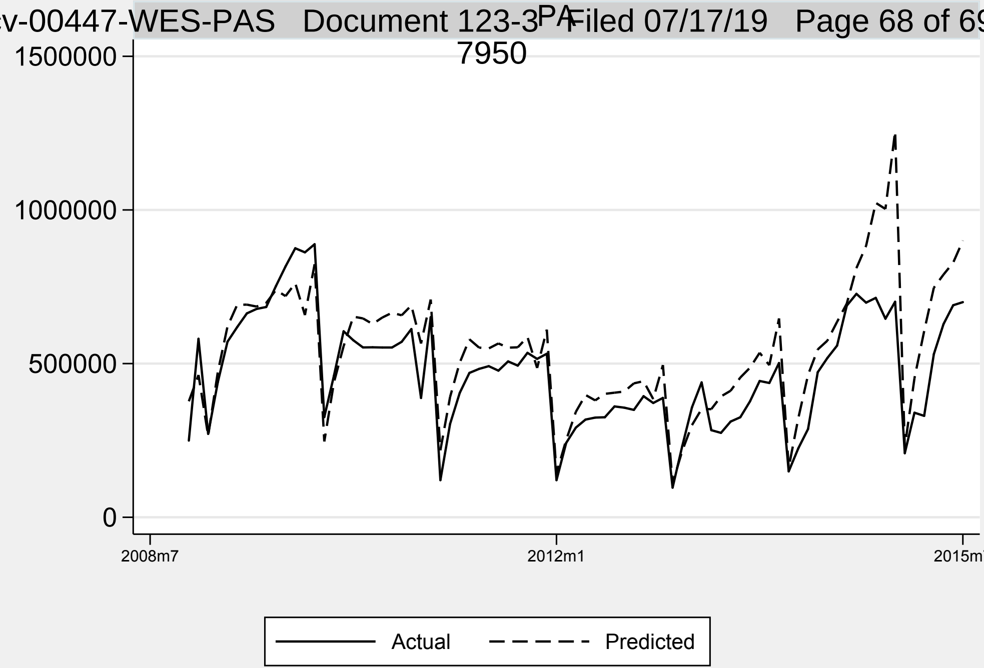
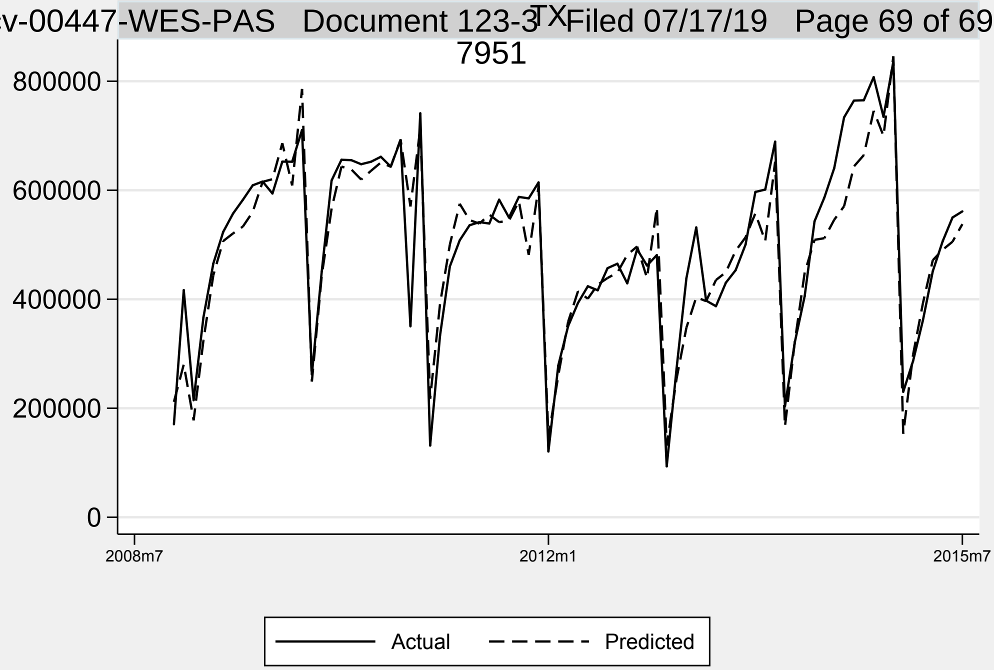
Actual
Predicted
Graphs by State



Graphs by State



Graphs by State